BIKE-SHARING SYSTEM DESIGN

Guidelines on conceiving and implementing a BSS as a public transport with a monocentric heterogeneous demand

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ABSTRACT

Bike-Sharing Systems (BSS) are spreading over the world at a fast pace. Several reasons base the incentive from a government perspective, usually related to sustainability, healthy issues and general mobility. Although there was a great prioritization in the last years, literature on how to design and implement them are rather qualitative (e.g. guides and manuals) while technical research on the subject usually focus on extensive data inputs such as O/D matrixes and other methods that may not be robust nor extrapolated to other places. Also, lack of data in some regions make them of little use to be easily transferred.

The thesis aims to work on an analytical continuum approach model to design a BSS, providing guidelines to a set of representative scenarios under the variation of the most important inputs. It is based on the optimization between Users and Agency, so there is a global outcome that minimizes total costs. In particular, it develops a monocentric approach to capture demand heterogeneity on cities center-peripheries.

The model is calibrated on Barcelona's existing BSS and results are within an acceptable error range for an analytical modeling. By optimizing its design, it is possible to see a big gap compared to the actual one. It would require a substantial increase in infrastructure (twice stations and bicycles), but would allow a much better Level of Service.

The scenarios results show the importance of demand density to the system. Low densities can rise sharply users' costs. It becomes particularly critical on societies of a lesser economic power (with a low Value of Time - VoT), where the affordability by its citizens or government can even compromise the BSS feasibility.

Regarding the central-peripheric relation, demand concentration within the central region benefits from Economies of Scale, although at a low level. Even so, infrastructure do not follow their relation in the same rate. The rise in concentration on the center does not imply in the same increase in infrastructure. The unbalance between zones rise the repositioning costs, but are considerably small compared to the system overall costs.

The thesis presents these results as an initial guideline to be used as references along with the modeling that makes them possible. The center-periphery differentiation can be seen both, as a reflect from the different characteristics from a region and also be used as steps to implementation of a BSS in phases, as it usually occurs.

Key words: Bike-sharing system; Design; Analytical modeling; Monocentric.

RESUMO

Los Sistemas de Bicicletas Compartidas (BSS) se están extendiendo por todo el mundo a un ritmo acelerado. Varias razones se basan desde el incentivo gubernamental, generalmente relacionada con la sostenibilidad, salud pública y movilidad general. A pesar de que hubo una gran priorización en los últimos años, la literatura sobre cómo diseñarlos e implementarlos es muy cualitativa (guías y manuales, p.e.) mientras que la investigación técnica sobre el tema generalmente se enfoca en el uso intensivo de datos y otros métodos que pueden no ser robustos ni extrapolables a otros escenarios. Además, la falta de datos en algunas regiones los hace poco útiles sin poder ser transferidos.

La tesis se propone a trabajar en un modelo analítico continuo para el diseño del BSS, proporcionando directrices para un conjunto de escenarios representativos, a través de la variación de los datos de entrada más importantes. El modelo se basa en la optimización entre los Usuarios y la Agencia, haciendo en la optimización que el resultado global tenga costos totales mínimos. En particular, la tesis desarrolla un enfoque monocéntrico para capturar la heterogeneidad de la demanda en el centro-periferia de las ciudades.

El modelo se ha calibrado con datos reales del BSS de Barcelona. Sus resultados se encuentran dentro de un margen de error aceptable para un modelado analítico. Al optimizar su diseño, es evidente la diferencia con relación al diseño actual. Sería necesario un aumento sustancial de la infraestructura (el doble de estaciones y bicicletas), pero permitiría un mucho mejor nivel de servicio.

Los escenarios muestran la importancia de la densidad de demanda para el sistema. La baja densidad puede aumentar considerablemente los costos del sistema. Esto se vuelve particularmente crítico en las ciudades de bajo poder económico (con un bajo Valor del Tiempo - VdT), donde la asequibilidad por parte de sus ciudadanos o gobierno puede incluso comprometer la viabilidad del BSS.

En cuanto a la relación centro-periferia, la concentración de la demanda dentro de la región central se beneficia de Economías de Escala, aunque en pequeño nivel. Aun así, la infraestructura no sigue su relación con la demanda en la misma proporción. El aumento de la concentración en el centro no implica el mismo aumento de la infraestructura. El desequilibrio entre zonas aumenta los costos de reposicionamiento, pero son considerablemente pequeños en comparación con los costos generales del sistema.

La tesis presenta estos resultados como una guía inicial para ser utilizada como referencia además del modelado que los hace posibles. La diferenciación centro-periferia se puede ver a la vez, como un reflejo de las diferentes características de una región. Además, el modelo podría utilizarse como *pasos* para la implementación de un BSS en fases, como suele ocurrir.

Palabras-clave: Sistema de bicicletas compartido; Modelo analítico; Monocéntrico

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LIST OF ABBREVIATIONS AND ACRONYMS

BSS	Bike-Sharing System
CA	Continuum Approximations
CBD	Center Business District
DV	Decision Variable
LoS	Level of Service
MaaS	Mobility as a Service
MHI	Median Household Income
PoI	Point of Interest
SUMP	Sustainable Urban Mobility Plan
VoT	Value of Time

1 Introduction

The chapter provides an initial overview on the motivations of the present work. The scope and its limits are stated to define an objective. The methodological approach that follows justifies the line of research adopted. Finally, it ends with the thesis chapter structure.

1.1 Context and relevance

Cycling is seen as a sustainable transportation and is becoming more and more discussed to tackle the urban problems that we bear from former transport policies on the last decades. The general idea is to focus on collective transportation and active mobility (Figure 1), i.e. walking and cycling. This approach becomes evident on the Sustainable Urban Mobility Plans (SUMP) that are found all over Europe or their equivalent for each region (e.g. NY Strategic Plan).

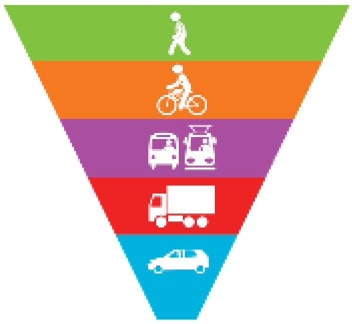


Figure 1 - General priority model for different transport modes.

Source: Malmo stad (2016).

The strategy is not done by chance, nor is the acceptance of cycling as a powerful engine for such changes. Bike-Sharing Systems (BSS) come along with this idea under a different approach from regular bicycle ownership. It is considered a need-base usage (Shaheen et al., 2010) although it does not behave as a renting service (Ricci, 2015) resulting in complementarity to general mobility. BSS bring benefits to a city in a number of ways: Reduce congestion and improve air quality; Increase the reach of transit (filling that critical gap between the station or stop and the final destination); Enhances mobility at lower cost (since it is much less expensive to the city than extending collective public transport service); Improve the health of the residents; Attract new cyclists (OBIS, 2011).

Besides, BSS have two key advantages when compared to other transportation projects: a comparatively lower implementation costs and project set up, from planning to inauguration (ITDP, 2013). From a government point of view, it is extremely appealing since it can happen within an election period.

Even so, traditional approaches of public/private transportation are limited in dealing with the increasing demand for mobility, which leads us to a new attitude towards established urban mobility concepts where a more flexible but affordable mobility is desired (Vogel et al., 2014).

The thesis tries to focus on the public aspect of mobility, recognizing its social benefits and economic restrains, natural to such systems. To cope with these trade-offs, one understands that the system requires subsidizes, which do not mean that a financial optimization is not necessary. Seen as a public good or basic service, it should be available to everyone, creating conditions to be distributed according to needs. In other words, "*urban equity in development implies that the urban space should not contribute to reproduce unequal relations or reinforce existing ones.*" (United Nations Human Settlements Programme, 2013)

In despite of the BBS flexibility, a correct system design makes a great difference in terms of future operation and maintenance. In addition, the planning is considered a small expenditure in comparison with the project implementation and system operative costs.

Systems Design is the main aspects of architecture, modules, interfaces, and data for a system to satisfy specified requirements. For the context of BSS, in this thesis, it means the infrastructure (i.e. stations and its spatial distribution) and components (e.g. bicycles, vans) that enable a certain Level of Service (LoS) such as probability of always finding a bike or free slot when needed.

As a first attempt of categorizing the system design on literature, two broad views can be easily identified. A first with qualitative information, references and averages parameters from few but relevant examples. Under this spectrum there are the Guides and Handbooks, providing a first approximation on ranges of values and main considerations for the whole system. Independently of the more detailed models, they present the fundaments of Bike-Sharing and no system design can be adapted without first revising some of the most important examples, treated on the coming chapter.

A second approach is the design models, where academic research relies and leads to more detailed and accurate results (although not necessarily one implies the other). Although there are numerous researches on Bike-Sharing on the recent years, they mostly focus on rebalancing problems. The ones that focus on system design usually require large amount of data and/or computational requirements but it is understood that few models have a compact methodology with reliable results and that can be compared to different scenarios.

The thesis tries to fill this gap by developing further an existing model where continuous approaches were used to have a perception between the trade-offs between Agent and User.

The strategy is to broaden the model through a set of scenarios where the most important parameters could be varied in order to identify which parameters can most alter de final system design. With the results, it is possible to capture the most marked output designs different cities could have.

Besides, another contribution is to add demand heterogeneity with center-periphery differences. It allows representing better the synergies that rely on demand concentration, common to city centers – mostly in Europe - and its impact on the system design.

1.2 Objectives

The purpose of this work is the development of a monocentric demand model to optimize Bike-Sharing Systems Design with continuum approaches. Specifically, the scope of the thesis is:

- Providing guidelines on how to design a bike-sharing system (BSS)
- Develop a monocentric continuum model to optimize BSS design
- Test it through sensitive analysis, exemplifying relevant scenarios
- Highlight the main trade-offs evaluating the most relevant variables that affect its design so the model can reflect different cities to draw design recommendations

It is considered out of the scope of the thesis: Demand appraisal; Rebalancing operations; Operational issues; Pricing schemes; and ITS.

The main assumptions correlates to the continuum approach methodology and are further explain in Chapter 3, but essentially, it can be resumed in a relative spatial homogeneity in terms of demand, behaviors, and costs with exception the above-mentioned center-periphery segregation.

1.3 Methodology

The methodology for the thesis started with research on general aspects of BSS. At first, the focus was on government guides and handbooks on European level, Latin and North America. Material in Spanish, Portuguese and English composed the main body of findings, with preference to the last.

The BSS Design focused on international journals, always in English, with most of the material found through the Elsevier platform. The core part of the model was extracted from a continuum approach methodology merged with another on centricity influence to system design.

From that, the theoretical development was elaborated taking into account the city of Barcelona, where data could be more easily found. System data is an open source available online and helped set demand patterns as well as calibration to the model. City data composed the final parameters to apply the model.

Finally, sensitive analysis helped to cover a wide range of possibilities without needing to emphasize and select one specific city or example.

1.4 Thesis structure

This work is structured in five chapters. After this introductory chapter, the literature review is presented to depict the state of the art of BSS Design. Some aspects concerning cycling and shared bicycle systems are detailed based on European and American guides. Firstly, there is a brief introduction to the history of the BSS and their characterization, where the most relevant aspects that influence bicycle use are highlighted, as well as success factors for bike sharing. Then, the focus goes on the system design, gathering information of previous works and how they tackled the problem. At this point is also introduced the centrality aspect in which this work is based. Additionally, some operational issues are briefly touched upon, with the objective of providing a closing overview and understanding of the system.

Following the literature review, chapter three describes the methodology adopted to achieve the objectives of the study, including sample definition and data collection. The equations, objective function and restrains are the core of this chapter, followed by the scenarios considerations and detailing aspects for future BSS.

Chapter four presents the results. It starts with the parameters considered followed by the model calibration so that the optimization can be done. Sensitive analysis will explore further the impacts of the inputs to the model and give ground to the different scenario typologies presented. The chapter ends with a qualitative discussion and future trends of such systems.

Finally, the last chapter brings the highlights of the present work, its limitations and introduces possible future research lines that can be followed from it.

2 Bike-Sharing Systems – A Literature review

This chapter reviews the literature of BSS and presents a brief state of the art on the system design with its most influencing factors. The system history is presented followed by the recent researches lines that surrounds it. The system design literature on BSS is analyzed and finally operational issues are discussed.

2.1 History

Bike-Sharing Systems (BSS) are spreading all over the globe in a fast pace. From a handful of schemes before the 2000's to over 1400 operating systems and 400 on the way (Chart 1), it shows signs of maturity as a service. Nevertheless, the system must not be taken for granted. As it is for any transportation system, it has its unique features and complexity. Up to date 150 of them ceased to exist indicating that its potential applications were not fully understood and it may not fit every scenario and context.

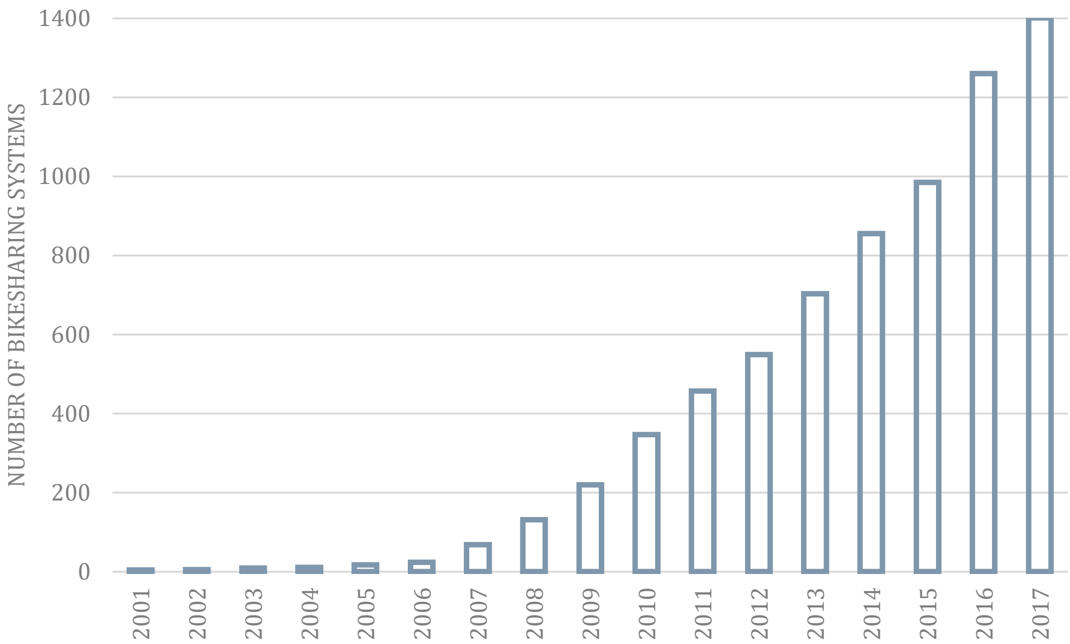


Chart 1 - Bike-Sharing Systems evolution around the world.

Source: Meddin (2014); Fishman (2015); www.biksharingmap.com

The system changed a lot from their first attempts on the mid 60's where regular bikes were let loose in Amsterdam for free usage – the White bikes (Midgley, 2011). The same author points that there were no incentives for taking care of bicycles so that vandalism and theft lead to the system closure. This was the first generation, and something had to change for the system to thrive.

The second generation began on early 90's, in Denmark. At first in small cities, until the system reached Copenhagen in 1995, where a large-scale system took place with several changes compared to the first generation. Bikes were specially designed for intense utilitarian use; there were space for advertisement on the wheels and the bikes could be picked up and deposited in special locations with a coin deposit (DeMaio, 2009). Although the system presented some evolution on organization, the anonymity was still a key issue to address.

The third generation would solve this bringing technology to the table on late 90's. Tracking the user, using "*electronically-locking racks or bike locks, telecommunication systems, smartcards, mobile phone access, and on-board computers*" (DeMaio, 2009). Even technologically solved, it took some years for its popularization.

A big push on the scheme came when Lyon implemented the system with 1500 bicycles in 2005, and two years later Paris, with 7000 bicycles (DeMaio, 2009). The system grew and kept evolving: some initiated the use of GPS, operators used networked self -service bicycle stations which communicated with a central computer system and Radio Frequency Identification (RFID) technology to monitor the location of bicycles in the system (Department for City Planning New York, 2009).

A fourth generation is still an open debate. DeMaio (2009) points a future where the dissemination of smartcards, mobile phones and kiosks screens driving a more efficient and sustainable usability, allowing new business models. Another direction agrees with this integration and add station modularity and mobility, demand-responsive approaches and use of environmental friendly technologies (e.g. solar powered stations and e-bikes) (ITDP, 2013;Mátrai and Tóth, 2016). With the recent advent, the dockless systems (i.e. free-floating) and transit smartcard integration (i.e. Mobility as a Service - MaaS) are also brought to the discussion (Parkes et al., 2013).

There is no consensus, but it might happen that each one ha part of the answer and this new generation, which is already on the way, will present all the previous aspects merged into the systems. Figure 2 brings a resume to the generation history, with highlights to the main attributes discussed.

First generation- Free systems (60's)	•e.g.: White bikes - Amsterdam •Regular bikes with diferentiating colour •Free access (Anonim) •Free usage •No fix stations
Second generation- Coin based systems (90's)	•e.g.: Bycyklen - Copenhagen •Custom bikes •Access with coin (Anonim) •Free usage •Fix stations
Third generation- ICT based systems (00's)	•e.g.: Vélos á la Carte, Rennes •Custom bikes •Access with user card •Free (usually in the first 30 minutes) •Fix station
Fourth generation systems	•Custom bikes – dockless station possibility •Access with mobilesand real time information •Free (usually in the first 30 minutes) •Large scale integration with different systems (MasS)

Figure 2 – Generations of PBS systems.

Source: adapted from Mátrai and Tóth (2016)

2.2 Characterization

Each transportation system has its ideal applicability in terms of population density, distance traveled, wealth of its citizens, weather conditions and so on. The strengths drawbacks must be weighted to see which model suits best each region. In the same way that a ubiquitous metro would seem unreasonable in terms of costs, a BSS may not be the best option to cover areas of great relative elevation in a city.

BSS is an individual transportation system, with relatively high accessibility in terms of spatiotemporal service operationality. It is also a flexible way of transportation, for it allows free movements to any other point in the system and without time constrains (such as bus and trains schedules). Its cost is regarded as low, at least when the systems are public or under a private-public partnership. The main drawback comes from the poor reliability that the system might have because there may or may not be available bikes or free slots for bicycle parking (Vogel et al., 2014) (Table 1).

The mode substitution is still an open debate as most users make it from public transportation or walking to BSS (Fishman, 2015) while there is also evidence of public transportation increase due to a last-mile integration. Anyhow, it is important the comparison between them since they are closely connected. Where the BSS is accessible, the collective public transportation is not. Nor it is flexible, having its predefine routes and timetables (i.e. spatiotemporally fixed). They also differ on reliability, for is most developed countries, they are expected to be mostly on time. Leaving the users cost as the only common point among them.

Table 1 - Classification of transportation and mobility services based on usage-oriented motives.

Motive	Public transportation	Private transportation	Carpooling	Shared mobility systems	Personal vehicle sharing
Usage	Collective	Individual	Collective	Individual	Individual
Accessibility	Low	High	Low	High	Low
Flexibility	Low	High	Low	High	High
Reliability	High	High	High	Low	Low
Costs	Low	High	Low	Low	Low

Source: Vogel et al. (2014)

This vision helps to understand their complementarity. BSS are relatively cheap, so the same user profile could be expected. In addition, while it may be harder to access the collective system, the BSS coverage is usually with closer spacing between stations. It is also quite flexible to reach different bus/train stops according to schedules, being the reliability the weakest link of such integration.

BSS fit one specific niche on the transportation supply system that a city must provide. Mátrai and Tóth (2016) place them as a resourceful last mile connector that enhances further transport alternatives (Figure 3). For that reason, they warn that the system does not usually provide alternative for commuters. This view fits with the previous table where one expects that the BSS cover local/urban trips that might connect to other transportations, but it is not guaranteed it can be an everyday transportation due to its doubtful reliability. For the same reason, ownership cycling is placed differently on the figure. It can be used in more often or even for much larger distances, while the BSS is limited by a defined boundary – the service region.

The figure also illustrates a clear overlap with some modes, such as walking and cycling. Fishman (2015) points out that the capacity from mode substitution from private vehicles remains a key challenge. In Montreal, BSS trips replaced 86% trips from other sustainable modes, which includes public transport (Midgley, 2011) and only 2% from private vehicles. In London BCH, UK—2%; in Vélo'v, Lyon, France—7%; in Bicing, Barcelona, Spain—9.6%; Capital Bikeshare, Washington DC, US—7%; Nice Ride Minnesota, Minneapolis, US— 19.3%; Melbourne Bike Share, Australia—19%; CityCycle

Brisbane, Australia 21% (Ricci, 2015). This should not discourage its implementation, but rather keep expectations realistic when trying to implement BSS, for as every transportation mode, it has its limitations.

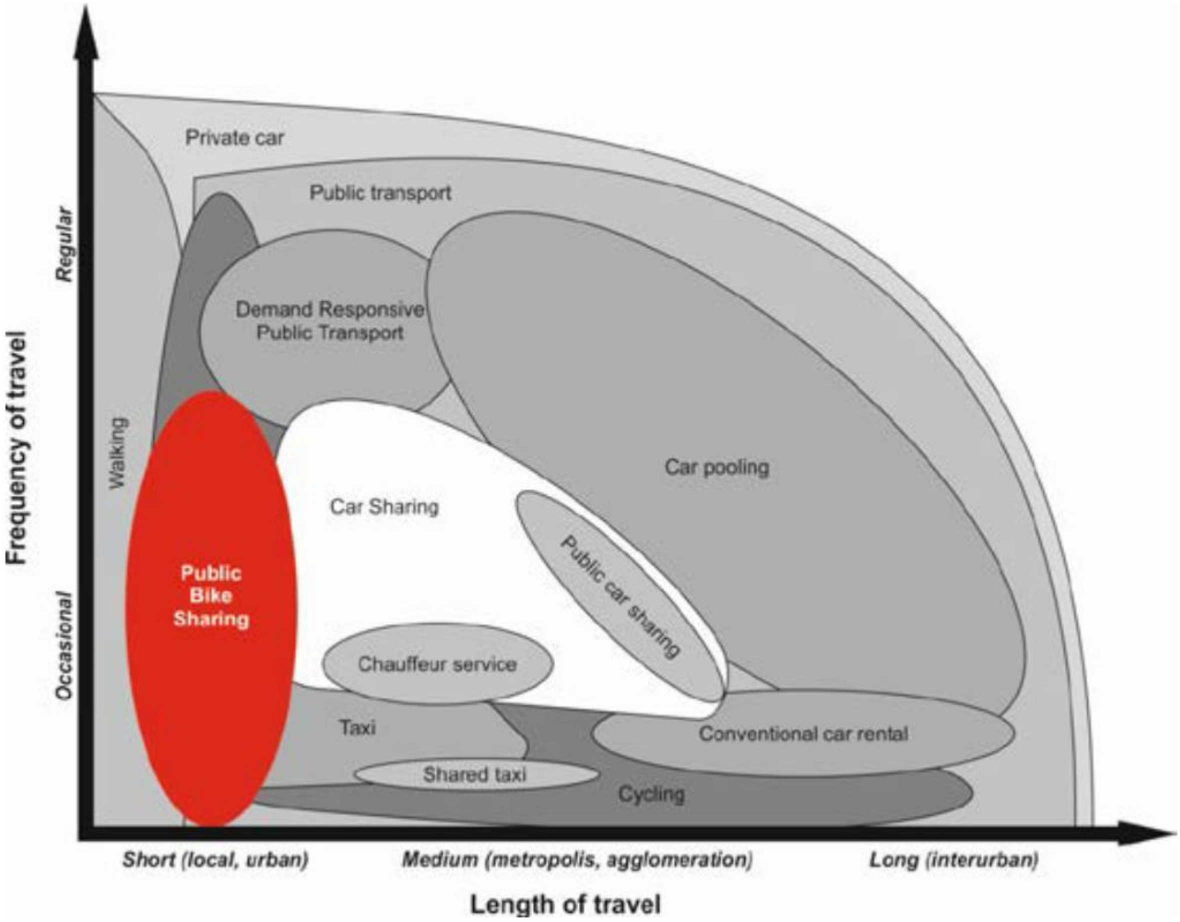


Figure 3 - Comparison of travel alternatives based on frequency and length.

Source: Csiszár, 2009; Tóth and Mátrai, 2015

Along the implementation over the years, publications tried to address how to design such systems or in analyzing the most famous existing ones. Here a problem rises for existing studies focus on particular aspects of one or more schemes, with different methodological approaches (Ricci, 2015). The author points out that the objectives of such systems are not always explicit nor can be rigorously checked which makes it difficult to attribute a system "success". One should bear it in mind when going through BSS benchmarking since there could be a very different system design when objectives from one city fall under a "public transport system for citizens" (Barcelona) and another goes for "promote short trips" (Göteborg) (Table 2).

Table 2 – Objectives of selected bicycle - sharing schemes.

System	Objectives
Barcelona, Spain	Improve interchange between different modes of transport and promote sustainable travel Create new individual public transport system for citizens' habitual travel needs Implement a sustainable, health-inducing service fully integrated with the city's public transport system Promote the bicycle as a common mean of transportation Improve quality of life, reduce air and noise pollution
Göteborg, Sweden	Raise the status of cycling Promote using bicycles for short distance trips
Lyon, France	Help create a more sustainable transportation system in the region by lunching a public bicycle system that provides a new mobility option for short trips Help achieve transport and land use planning objectives including pollution, emission reductions, reduced traffic congestion, road and parking cost savings, consumes cost savings, energy conservation, reduced crash risks, improved public health, and support for smart growth land use development
Montreal, Canada	Encourage the use of public bicycle instead of cars for short, inner-city trips
Paris, France	Act on air quality and public health Improve mobility for all Render the city a more beautiful and agreeable place to live Encourage economic vitality Reinforce regional solidarity
Washington DC, USA	Provide as many transportation options as possible and reduce the level of congestion, especially downtown

Source: Midgley (2011)

Going a little bit into the system, one can see major characteristics that differentiate the multiple manifestations that the BSSs present. It is necessary to see them so one can have a better comprehension of which characteristics fits better certain objectives. On Table 3, Vogel et al. (2014) shares a taxonomy of these possible attributes:

Table 3 – Taxonomy of BSS business models.

Features	Manifestation
Automation	Manual; Automated
Operator	Public institution; private company; public-private partnership
Pricing	Linear; progressive; flat-rate
Design	Station-based; station-less
Spatial Flexibility	Round-trip; one-way; free-floating
Booking	Reservation; spontaneous

Source: adapted from Vogel et al. (2014).

- Manual or automated: where the requirement of personal/staff is the differentiation between the two modes, which can be technologically equipped to track the use and monetary transactions. In Spain, for populous and/or dense cities, automated systems were preferred (IDAE, 2007).
- Operator: classically divided by three main Business model – Public; Public-private and fully Private – each has its advantages and drawbacks (Table 4). Vassimon (2015) gathers data from 50 different BSS across the globe and compare such models. Mainly private model differs the most from the other two in their size and reach – private ones have smaller systems, with less bikes and serve less people – which is understandable in a company that seeks profit. The author caveat was that it does not mean it is a flaw system, but may not fully serve as the purpose of a public transportation mode.
- Pricing: usually differentiated in a registration fee and a usage fee, based on time and with linear or progressive price increase. It is common that the first 30 minutes are free to incentive bike usage. Also, since pricing has a big effect on the intended users, different strategies can be used, such as a high registration fee with low usage fees to incentive commuters (Vogel et al., 2014).
- Design: distinguished between station based, where vehicles are only accessible on specific locations and station-less, with a designed service area. The former limits user's spatial accessibility, it simplifies rebalancing operations significantly.
- Spatial flexibility: the two-way model binds the user to return to the same station where he picked up the bicycle whereas on the on-way the user is free to return it to different stations.
- Booking: may be spontaneous on a first-in-first-served base or with reservation through an app some minutes before arrival. It is important to note the trade-off with a better reliability when reserved by affecting spontaneous trips and having an idle vehicle for that period.

Table 4 – Business models for a bike sharing from the municipality point of view.

	Advantages	Disadvantages	Operator examples
Public	Autonomy on decisions Revenues streams from fees and memberships	Requires a more "hands on" approach Requires public funding	OV-fiets (Netherlands) DB Bahn: Call a Bike (Germany)
Public-Private	Requires little or no public funding Balance between autonomy and costs	Forgone revenues due to advertising space lost Cannot take part in every decision	JCDecaux (multiple countries) Clear Channel (multiple countries)
Private	No initial investment needed No ongoing maintenance costs No need to plan or operate	Distant from system operations and outputs Follow-up to align interests Cannot take part in decisions	NextBike (multiple countries) Banco Itaú (Brazil)

Source: adapted from Midgley (2011); Shaheen et al. (2010)

This study will focus on automated, public or private-public, station based bicycle-sharing systems.

2.3 System design approaches

The different methodologies and paths used from public bodies and researchers are to contribute to the development of the system.

From the public side, it is more common the use of manuals, guides and handbooks as a general orientation to the system design. Good examples are: *OBIS Guide – Optimizing Bike Sharing in European Cities* (OBIS, 2011); *The Bike-Share planning guide* (ITDP, 2013); *Public Bike-sharing systems for Latin America* (Montezuma, 2015). The information reflected major metrics to the system, such as: average distances between stations; ranges of penetration to the system demand (based on population), costs for different gammas of bikes and stations.

Their goal is to go through the whole implementing process, discussing how to set objectives, orientations to tenders, stakeholders' involvement, financial models and so on. It is comprehensible that such descriptions must fit a wide range of scenarios and may not go deep into the system design parameters. Even when major metrics are provided, they show a significant difference when confronted with operating systems (Table 5). Most BSS operate at lower levels than recommended and while it is understandable for some schemes to not meet stipulated satisfactory performance baselines, if almost every scheme fails to reach the minimum values it means that these values are not completely adequate (Vassimon, 2015). Another interpretation could be that current schemes have poor LoS for their users and the main parameters should be more strictly steered on bidding processes. However, at what cost?

Table 5 - Comparative system design metrics - theory to practice.

Performance metric	Target efficiency level (ITDP, 2013)	Global performance average from 50 BSS (Vassimon, 2015)
Station density (st./km^2)	10 - 16	4 - 11
Docks per bicycle	2 – 2,5	1,72
System efficiency (uses/bike.day)	4 - 8	3,5

Source: adapted from Vassimon (2015)

Guides may bring costs related to some aspects per thousand inhabitants or bikes in the system. OBIS (2011) states that implementation could go from 2.500 to 3.000 € per bike while operating costs would be around 1.500 to 2.500 €. Montezuma (2015) gathers implementing costs from a number of schemes on different countries according to the different gammas that a BSS can have (Table 6).

Table 6 - Approximate prices per station according to their sizes and gamma level, in USD.

Station Size (slots) / Gamma	Basic Gamma	Medium Gamma	High Ending Gamma
Small (10 slots, 8 bikes)	15.900	25.400	41.000
Medium (15 slots, 12 bikes)	18.800	33.150	47.500
Big (20 slots, 16 bikes)	28.315	37.315	59.000
Cost per Km^2 (9 terminals, 3 of each size)	189.045	287.595	442.500

Source: Montezuma (2015).

If these references are applied in Barcelona's BSS - Bicing, with its 6000 bikes we would have operational costs from 9,0 to 15,0 M€ according to OBIS (2011)'s parameters when real numbers are estimated over 14,6 M€/year[1]. Regarding implementation costs, values for the 420 Bicing large stations go from 11,9 to 24,8 M€ according to Montezuma (2015)'s parameters when estimated values were placed on 15,9 M€. From

[1] http://blogs.elpais.com/eco-lab/2011/12/cuanto-cuesta-un-sistema-de-bicicleta-publica.html

that one can understand that such guides are good as a first estimative and grasp the Order of Magnitude from BSS's costs, but could not be strictly followed much longer on an implementation process. Since the values are rather static, nor can they represent the main trade-offs such as station density and LoS or more bicycles or repositioning vans.

The range of references also appear for other important aspects such as a market penetration of one daily trip per 20-40 residents; station densities from 10 to 16 per square kilometer; and 10-30 bikes per thousand resident (ITDP, 2013). Bicing values would be 1/20, 8 and 7,5 respectively which corroborates with the previous point: the parameters are to be considered references but could never capture every specificity of each system.

Academic research comes along with more methodological, objective and quantifiable approaches if compared to guides. Literature review shows that major differences between them vary on the volume of inputs needed, computational requirements to reach solutions and the degree of detailing for the outputs.

The GIS & Data modeling are often heterogeneous and adapted for each specific need. Each station location, size, region demand is determined through extensive databases. At the same time, not every city may dispose of such information making solutions local. The strengths of this kind of modal is this adaptability to the very specific situation of one place. On the other hand, little can be extrapolated to new scenarios for completely new databases are required.

García-Palomares et al., (2012) highlights the costs of obtaining O/D matrix through surveys and construct a detailed activity based demand attract/generate model. It is data intensive since they use mobility data, cartography, slopes, speeds, population and jobs at a building level. Then, it is applied the location-allocation models for the station, their size is calibrated through the related demand. They try compare solutions minimizing impedance (where the sum of all of the weighted costs between demand points and solution facilities is minimized) or maximizing coverage according to demand. Results show diminishing returns in accessibility for increases of station density.

Chen et al., (2015) also point out the expensive O/D matrix and builds their through open data maps, check-in datasets such as Foursquare API and demographic data (Figure 4). They are able to calibrate their model with the existing BSS in Washington (USA) and Hangzhou (China) and draw a user profile and Points of Interest (PoI) from each city. It is interesting to note how PoI differ greatly from each city, for where transit matters most for Washington's BSS, Dinner and Meals category stands out for the Chinese counterpart (and transit is the 8th). It shows that each cities have their own dynamic and needs rather than the "One-size-fits-all" approach. Finally, they test their model offline to check its accuracy and reach 80-85% of demand predictability with low computational time (12 seconds). The station location follows from where there is more demand and no further detailing in station size or system cost is given.

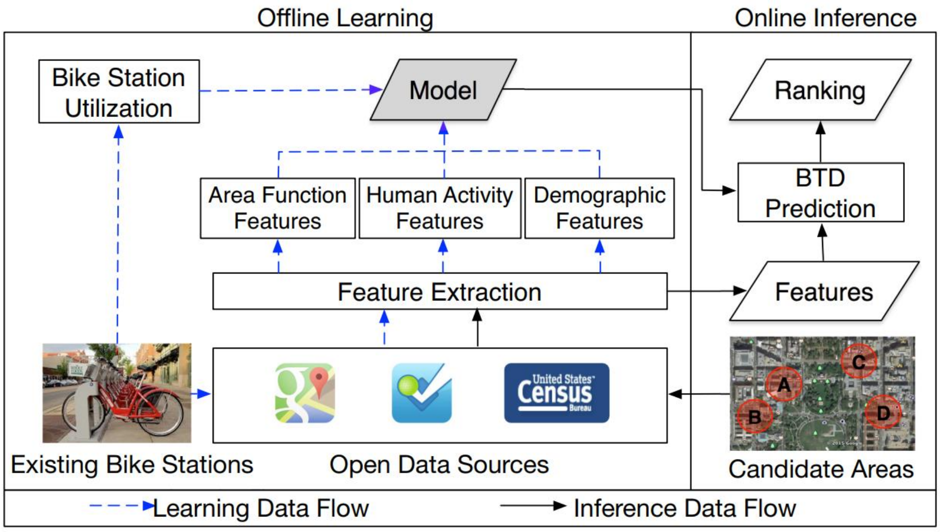


Figure 4 - Overview of the methodological framework.

Source: Chen et al. (2015)

<u>Operational Research</u> modeling stands for a mid-ground on the system specificity. The idea is to use programing to achieve goals such as maximize demand attracted or covered area. It is timing consuming to set the programing, but once set it will usually provide quickly results and variations. Nevertheless, studies with this methodology still require considerable data availability at detailed level, such as Origin/Destination matrixes, which make solutions local.

Lin et al., (2013) state that the problem requires an integrated view considering Agency and Users' Cost and goes for a Hub Location and Maximum Covering model. For the User perspective, LoS come from this coverage provided along with the availability of the system of request – return availability is not considered. Their model assumes an O/D Matrix an input and bring as result through greedy heuristics station location and bicycle paths (links) used – which is an important demand enhancer although not controled by operator unless it is a public administrator. Nevertheless, costs on rebalancing, operation and maintenance are neglected which limit a more holistic evaluation.

Martinez et al., (2012) models individual trips in space and time with fixed and variable infrastructure costs to maximize revenue when setting the system variables . Station potential placement is determined using a traditional p-median problem. The authors use a Mixed-integer linear program to reach optimal location of stations and fleet size through heuristics. Demand was simulated and calibrated by the metropolitan department which was further filtered by a discrete modal share applied to the bicycle.

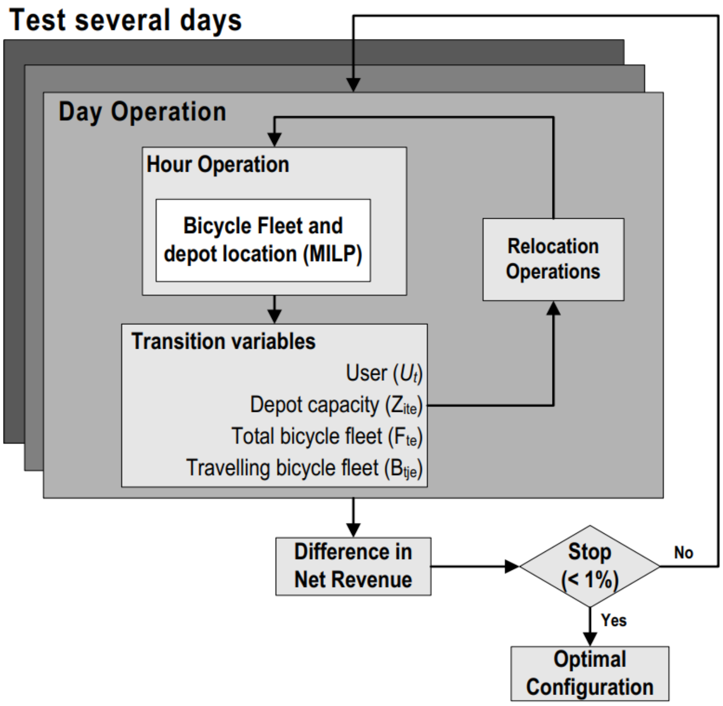


Figure 5 - Bike-sharing planning system model framework.

Source: Martinez et al. (2012)

Continuous Approximations (CA) modeling characterizes variables as continuous (opposed to discrete) to perform optimizations in a system. It smooths major contrasts for the sake of simplicity and a quick result. If it is correctly conceived and calibrated, the particularities of each sub region may result of minor importance to the whole system overall and an average good solution can be found. Analysis shows that CA can yield a location design very close to the true optimum (Carlos F. Daganzo, 2005). It allows quick analysis insights in the problem structure (Li et al., 2016) such as the measure of a system's trade-offs.

Besides, robustness is one of its features, for even with certain variation on the inputs, the solution is not dramatically changed. Its drawbacks rely when the inputs variability is heterogeneous enough to result in significant loss in accuracy in a discrete level or when further detailing is needed and the global outputs are of little use.

It is one assumption of this work that in a BSS design both drawbacks are of little importance in most cases. Although differences between regions' demand do exist, the requirement of a minimum system coverage and the proportional smaller cost of enlarging one station in comparison with the installation, make it feasible the continuous approach with a small number of D.V.

Li et al., (2016) proposes a Continuum Approximation model for design of a one-way Electrical Vehicle sharing system that serves a metropolitan area. The model determines the optimal station locations and the corresponding fleet sizes to minimize the system cost, including station construction investment, vehicle charging, transportation and vehicle balancing, under stochastic and dynamic trip demands. They compute users cost as access and a no service penalty and the agency considers the infrastructure and a fixed unitary rebalancing cost (considering that the systems is reorganized every 24h).

According to the authors, the system cost optimization is still complex for the spatial discretization. On their analysis of the Sioux-Fall network in the USA, they compare the solution to a discretized solution and find out that errors are small (and should be smaller for bigger networks). When doing a sensitive analysis, they highlight that the walking unitary cost has significate impact on station density but not as much in fleet. Along with it, they also state that the vehicle cost has a big impact on the system design. As unexplored points there are the variation on rebalancing period and that there are no Economies of Scale when demand is varied.

Llopis (2016) gathered several inputs of system cost and users behaviors to model Barcelona's BSS Bicing. Through a service region, with a slope and a certain demand, her work gave base to a good calibration after a few corrections and showed an optimal solution with more stations and a better LoS, but at a higher cost. It also demonstrated the robustness of the model, with small variation to the system design when small changes to the inputs were considered.

The work left some questions unanswered which could be further explored. If the continuous approach could express the main variables of a system in a quick and reliable way, why not verify the applicability to other scenarios and grasp the general design when the most important inputs are varied?

This last model was chosen to be further developed along with other incremental measures to try to compensate the drawbacks and better represent a BSS.

Table 7 summarizes the literature review, structuring the approach, most common inputs and outputs selected. From it, it is possible to see that O/D matrixes are in most the works seen, demographics are used mostly in GIS & Data approaches as well as other data sets such as topography. For the O/D matrixes, some authors had to extract them from global matrixes and then do a modal split to the bicycle use, showing that before a BSS exist, it is unlike that accurate data is available. Temporal demand is not commonly explored and when it is, it is focused on the day period, disregarding seasonal variations that are quite significant for a BSS as presented further ahead in this work.

As outputs, most works seen try to position each station, most quantify bicycles needed and hardly none explore the repositioning is terms of vehicles needed or time windows to perform the operations.

To reach solutions, approaches that focused only in coverage disregarded costs but the ones that tried a cost optimization approach gathered User and Agency costs for doing so, with one exception.

From this overview, one understands that system design methodologies and parameters considered are not unanimity (nor should they be). While some authors focus the problem as station placement, others they to consider different aspects that also affect the system.

Table 7 – BSS design models classified by solving methodology and required inputs / outputs.

Models	O/D Matrix	Demographic Data	Other Data sets	Temporal Demand Variabliity	Exact Station location	Station size	# Bikes	# Rep	Agency Cost	User Cost	Authors
Qualitative / Guides	○	●○	○	○	○	●○	●○	○	●○	○	*IDAE (2007), Obis (2011), ITDP (2014), Montezuma (2015)*
Continuous Approx.	●	○	○	●	●	●	●	○	●	●	*Li et al (2016) - Carsharing*
	○	○	●○	●	○	●	●	●	●	●	*Llopis (2016)*
Strategic Design	●	○	○	●	●	●	●	○	●	●○	*Martinez et al (2012)*
	●	○	○	○	●○	○	○	○	●○	●	*Lin et al. (2013)*
	●	○	○	○	●	●	●	●○	●	○	*Frade, Ribeiro (2015)*
GIS & Data	●	●	●	○	●	●	●	○	○	○	*García-Palomares et al. (2012)*
	●	●	●	●	●	○	○	○	○	○	*Chen et al (2015)*

A system approach evolution can be seen. While guides give a first panorama to the BSS world and are able to give orders of magnitude to the problem, CA and Strategic Design can be a first attempt to implement the system in broad level. GIS & Data may fit into a system calibration and improvement when systems are already running and there is abundant data.

2.4 Aspects that most affect BSS design

Characteristics that influence the business model and thus the design can be divided into endogenous and exogenous factors (OBIS, 2011; Vogel et al., 2014) (Table 8). By exogenous factors, it can be understood the characteristics outside the system itself, belonging to the city and that cannot be influenced / changed (e.g. climate, geography) or have a long-term modification (e.g. population density, mobility behavior).

Meanwhile, endogenous factors are adjusted to fit this determined exogenous characteristic a city has (Vogel et al., 2014). They can be further divided into the physical and institutional design. The first comprises the technological part such as software, user cards and other IT aspects, while the service design comprises system size and density (of stations), service availability, target groups and pricing strategy and so on (partially coinciding with this work definition of BSS design). The former, institutional design, are business related definitions that have legal implications – setting responsibilities among stakeholders - and financial aspects guaranteeing sustainability on the long term.

The exogenous factors are a combination of city characteristics and population behaviors and greatly influence demand. While some are rather physical (e.g. region extension, topography, transport infrastructure) others are behavioral (e.g. mobility patterns, economic power for accessing other transport options).

Table 8 – BSS influencing factors.

Endogenous factors		Exogenous factors
Physical design	Hardware & Technology	City size
	Service design	Population density
Institutional design	Type of operator	Mobility behavior
	Contracts and ownership	Climate
	Financing sources	Demographic factors
	Employment opportunities	Economic factors
		Geographic factors and topology
		Existing infrastructure
		Financial situation

Source: Adapted from OBIS (2011).

2.4.1 Endogenous Factors - Service Design

Early in the chapter it is discussed the different objectives local authorities may have when implementing BSS. Common to all forms of system design is the need to understand which users to focus on – the target groups. While commute trips for work and education require a dense station pattern and a preference concentration on business districts and living quarters, system that wish to attract tourist trips should focus also in Points of Interest (Table 9).

Each of these segment can reached through different communication channels and pricing strategies (OBIS, 2011) and one can understand use complementarity from them. For example, trips related to leisure are more common during weekends while work and education are usually during weekdays. One must bear in mind that if the infrastructure is already placed, the adequate use of the system justifies its existence by avoiding unnecessary idle periods.

Table 9 – Trip purpose (target users) and their Requirements & Problems.

	Work and Education	Leisure	Errand	Tourism
Requirements	Dense station network Station near PT stations and living quarters Bikes and slots available	24/7 service Safety during the night	Dense station network Lock on bike	Station near PT Station near Points of Interest
Problems	Lack of rush hour availability	High prices for longer rental	Lack of options to carry goods	High prices for longer rental

Source: OBIS (2011).

This first decision will help driving the followings on system design. Its size and density are the number of bicycles; station size (docking points per station); and number and density of stations. They are determined by the size of the city or region selected, the target groups and goals (OBIS, 2011). Other factors come along in a holistic approach to be consistent with the objectives. For example, a system with the objective of complementing work and education trips should have a dense network, not necessarily 24/7, focus on monthly and yearly registration, with a pricing strategy the enhance long term users and with fairly public transport integration. Table 10 expands these factors to be taken into account.

Table 10 – Endogenous factors to be decided when implementing a BSS.

Size and density	Availability	Registration	Pricing	Information	PT Integration
Number of bikes Number of docking points Number of station Station Density	24 hours or limited Service seasons: year-round or limited	One-time Daily Weekly Monthly Yearly	Period free of charge included Increasing or decreasing price per time unit	Websites Apps Maps Terminals	Information integration Physical integration Access & charges

Source: Adapted from OBIS (2011).

Daily availability will mostly depend of the city/system size. Large ones tend to provide a 24-hour service, while smaller cities tend to close the service during the night (OBIS, 2011). On the other hand, year availability relates to weather since harsh winter brings demand down and there is no point in operating the system. This topic will be revisited on the exogenous factors.

Regarding pricing, registration and usage fees are distinguished and combined to follow a strategy. Nevertheless, pricing models may vary considerably and usually try to maximize utilization rates (Vogel et al., 2014). For example, pricing structures that incentivize short trips maximize the number of trips per bicycle per day (ITDP, 2013). For that reason, it is common that the first 30 minutes of usage are free (OBIS, 2011), internalized in a longer period in a smaller registration fee, which favor commuters. After this free-of-charge period, it is common that fees increase exponentially, as a way to encourage short trips (ITDP, 2013) (Figure 6).

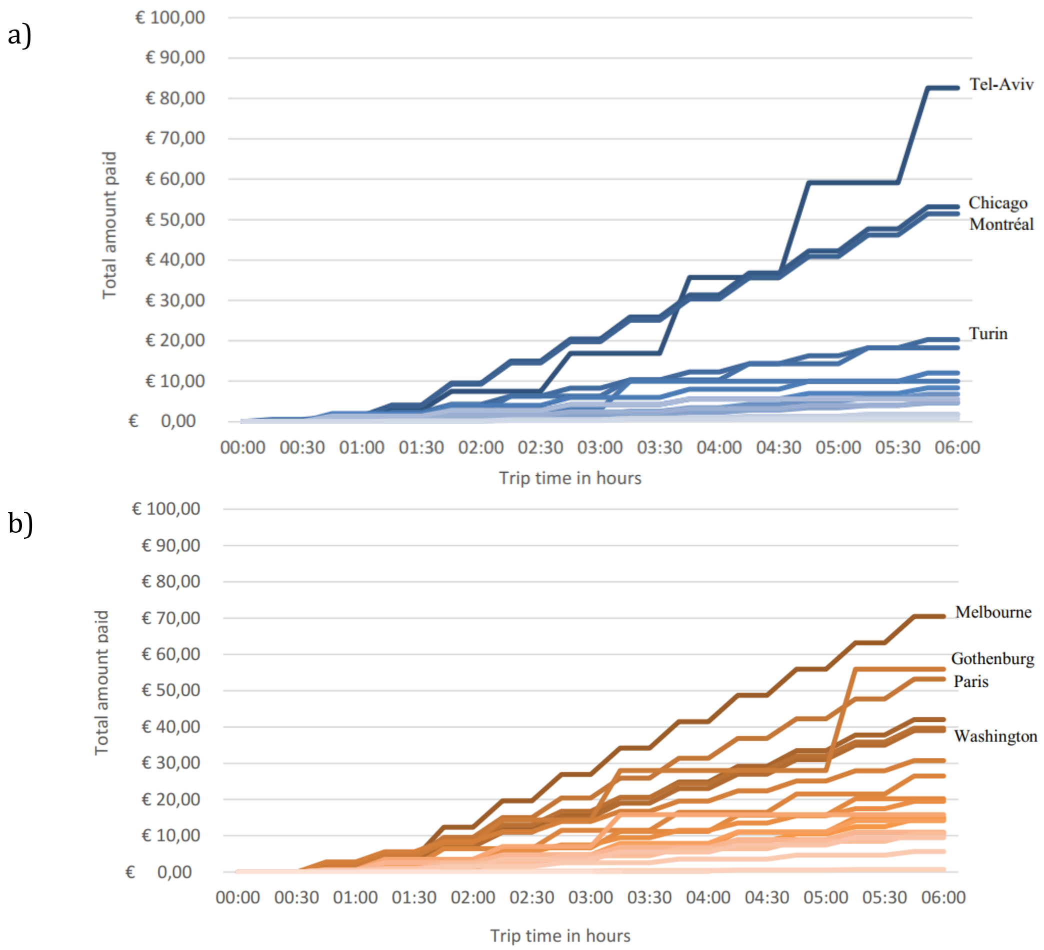


Figure 6 - Fee structure for a) public and b) private business model schemes.

Source: Vassimon (2015).

Information channels are also an important factor to enhance BSS, but beside the mainstream ones such as websites and maps, apps are doing a big advance when it comes to real time remote communication. Most important of all for the routine customer journey is the need to know where there are available bicycles to pick up and drop off. Therefore, the idea is that information should be widely available and easy to understand to all users.

Closing up the Endogenous factors is the system integration to other means of transport: Mobility as a Service (MaaS). Even so, while public (and private) entities cannot assure this holistic integration, favor the public transport (PT) is already an important step. Ricci (2015) attributes part of Lyon BSS success in generating cycling journeys to a public transport integration, spatially and through the pricing policy. Integration may help to relieve PT during peak hours, be present in areas where it does not cover all mobility needs (OBIS, 2011), besides being an important last-mile connector (Shaheen et al., 2010).

2.4.2 Exogenous Factors

2.4.2.1 Region size

A region size can be comprehended by either its physical dimensions or people covered. ITDP (2013) suggests defining a coverage area as a first step to design a BSS demand and recommends a minimum of 10 km². Although a minimum threshold is not mandatory, it makes sense such advice. Small schemes could not cover areas large enough to serve the users' daily mobility needs (ITDP, 2013; OBIS, 2011).

As a policy recommendation, Bührmann (2007) suggests a minimum 200 thousand population to support an automatic BSS which coincides with IDAE (2007)'s guide. When only population is taken into account, OBIS (2011) sees different characteristics and outcomes for BSSs of different size in their analysis of 51 schemes. Cities transports' modal split, usage fees strategy and daily availability are among them but some major KPIs where not significantly different (Table 11). This result coincides with Vassimon (2015) analysis of 50 BSS where population size could not explain important metrics like the number of station or bicycles per inhabitants (Figure 7).

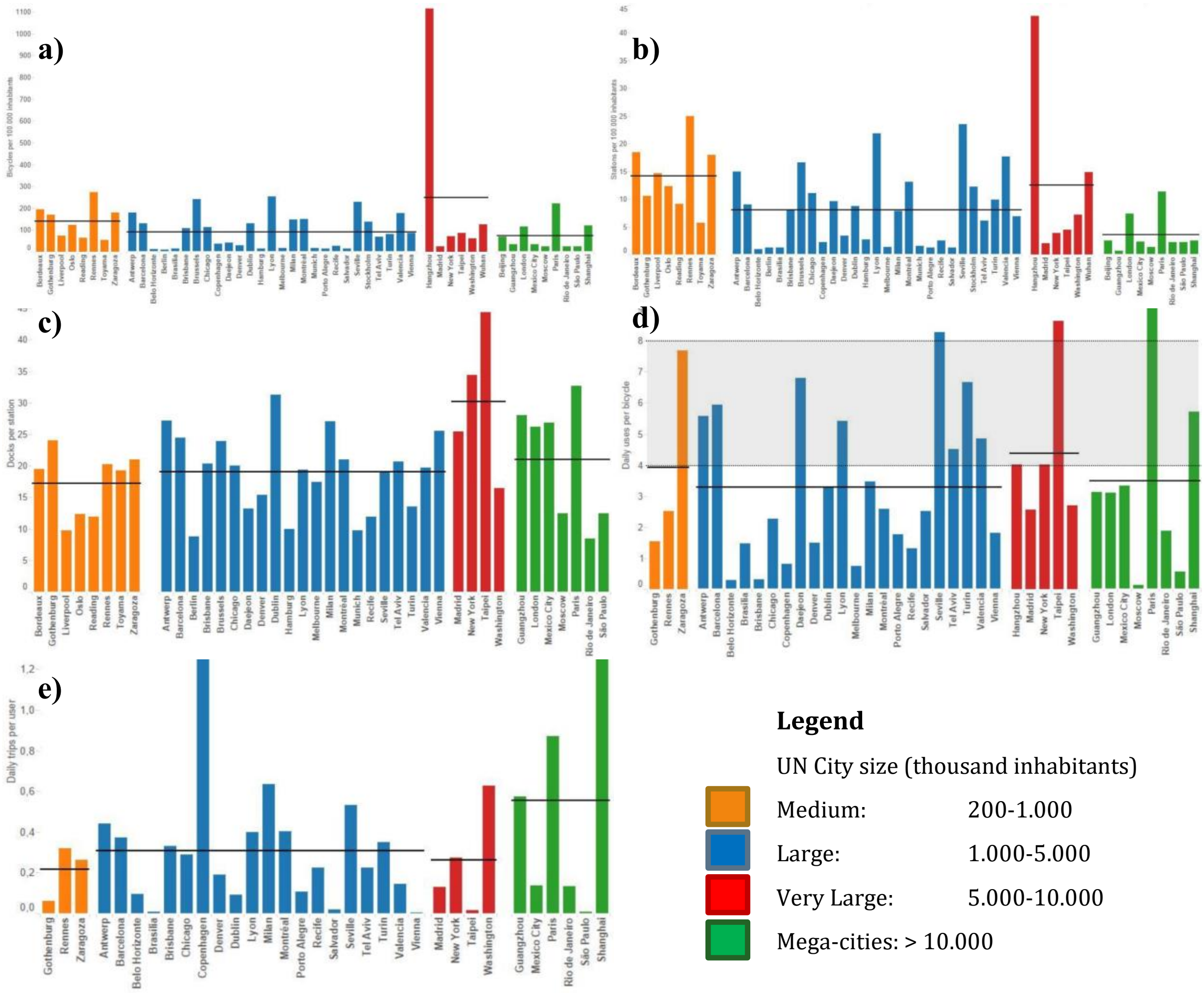
Table 11 - Average of BSS KPIs in the OBIS Sample.

	Small cities	Medium cities	Large cities
Bikes per 10.000 inhabitants	14,0	14,4	15,6
Stations per 10.000 inhabitants	1,8	1,3	1,5
Docking points per bike	1,2	2,0	1,7
Bikes per station	22,9	23,5	9,5

Source: Adapted from OBIS (2011).

Although both works use different definitions of city size (the first considers large city as anything bigger than 500.000 inhabitants), the conclusion is the same population does not explain major system design parameters. In Figure 7, averages are mostly similar or do not present linearity and standard deviations are visually considerable. Therefore, another factor must affect the system design, which cannot be explain only by the region total population.

Several authors also see relevance in the population density (IDAE, 2007; Montezuma, 2015; OBIS, 2011; Transport Canada, 2009) although no deeper comparison study was found with this factor as with population absolute size. There are insights of its impact such as OBIS (2011)' consideration the schemes in cities of low population but high density could hold automated system but numbers were not explored.



a) Number of bicycles per 100.000 inhabitants; b) Number of stations per 100.000 inhabitants; c) Average docks per station; d) Average daily uses per bicycle; e) Average daily trips per registered user.

Figure 7 - Comparisons of different BSS KPI metrics by different city cluster size.

Source: Vassimon (2015).

Hence, there is a literature gap where more attention should be given to the relation of population density and region dimensions all together. This is a known factor for the success of urban infrastructures since a larger share of inhabitants can benefit from it.

2.4.2.2 Population and job density

Population density has a high impact on a BSS. It is recommended that the system deployment be on areas with a high concentration of people with the exception of city centers or 'downtowns' (Transport Canada, 2009). The authors comment that the reason for that is that they usually present several other attributes that generate a large number of bicycle trips, concentrating high employment densities, being rich in retail and entertainment services as well as in public facilities (Figure 8). This was further confirmed by several authors, which associate population and job density as a significant factor for usage rates at different times of the day / week (Evans and Moskowitz, 2012; Faghih-Imani et al., 2017; ITDP, 2013; Médard de Chardon et al., 2017; Ricci, 2015).

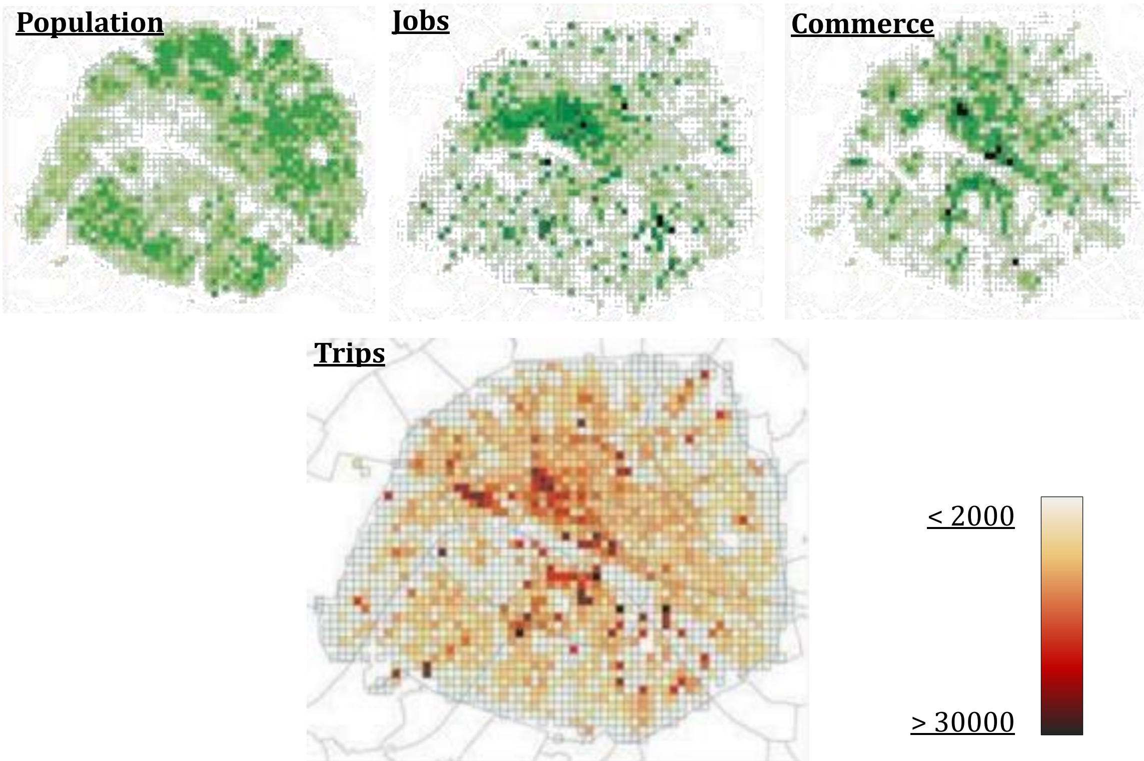


Figure 8 – Paris demographic data and corresponding demand by day.

Source: Adapted from Montezuma (2015).

Besides, population density also reduces rebalancing needs for both refills and removals, it has a smaller impact on the arrivals during the morning compared to other periods of the day (Faghih-Imani et al., 2017). It enhances public transportation use where it is not a good option by being a first / last mile connector although it may take away public transport trips in core urban areas well served by it (Ricci, 2015). But rather than focus on one or the other, when both coincide, i.e. dense mixed-use areas, they are likely to attract and generate the most demand for a BSS (ITDP, 2013).

An alert to this density rule is when there is an external demand. Commuters and tourist may be an important proportion of users and do not necessarily relate to dense population and job areas, for they have different needs (Médard de Chardon et al., 2017).

2.4.2.3 Points of interest

Alike the population and density, regions with significant points of interest (POI) also experience higher arrivals and departures (Faghih-Imani et al., 2014). What is considered a POI may greatly differ from city to city, mainly to different cultural aspects. For example, while cafés and restaurants play a big part in Washington BSS demand, in Hangzhou they are at the bottom of the top 10 list (Chen et al., 2015). On the same analysis, one sees Hospital or Karaoke as very relevant to this Chinese town, while it is not even listed in the American counterpart (Table 12). This highlights the precaution on a blind model export without understanding the city and region dynamics.

Public entities and bike-sharing designers must be aware of such biased choices that enhances the system demand. For example, concentrate stations on cultural points only attract one type of demand (Ricci, 2015) and if the objective is to promote a more equitable access, station placing must go beyond these specific points. Transportation engineers shall help providing such relevant information but ultimately it is a political decision on how to focus a system.

Table 12 - Top-10 POI categories most relevant to station utilization (w/ correlation coefficient).

	Washington, D.C.	Hangzhou
1	Café and Bakery (0,53)	Residential area (0,65)
2	Bar and Restaurant (0,52)	Vegetable market (0,57)
3	Hotel and Hostel (0,49)	Hospital (0,55)
4	Work Place (0,45)	KTV (Karaoke) (0,51)
5	Residential area (0,38)	Hotel and Hostel (0,49)
6	Retail store (0,35)	Retail store (0,45)
7	Bank and ATM (0,34)	Work Place (0,41)
8	Law firm (0,32)	Bar and Restaurant (0,38)
9	Gym and Yoga (0,31)	Hair salon and Spa (0,31)
10	Museum and Gallery (0,25)	Movie theater (0,29)

Source: Chen et al., (2015).

2.4.2.4 Geographic factors and topology

A region topology affects BSS by the tendency cyclist have of going downhill but refusing to go up depending on the slope. As consequence, stations at higher elevations tend to go empty while those at lower elevations are more likely to fill up (Midgley, 2011). Slopes bigger than 8% may represent a red flag for the implementation of a BSS while being bellow it could be tackled with electrical bicycle (e-bike) fleet or a high number of repositioning fleet (Table 13). Nevertheless, no study was found quantifying how much e-bike can enhance uphill travels to clarify the trade-off.

Table 13 – Advisable system according to the region slopes.

Slope	System
Slopes > 8%	Difficulty for a public BSS succeed
4% < Slopes < 8%	Electrical bicycle fleet
	Repositioning from low to high elevations
Slopes < 4%	Likely for a public BSS succeed

Source: IDAE (2007).

2.4.2.5 Climate

The weather may influence the BSS usage in two ways. Along the year, demand may change according to seasons whether it is by temperature or rainy seasons (on tropical zones). On temperate zones, where most BSS are, it peaks during spring and autumn mostly, with smaller activity during winter and punctually a vacation month. It is worth noticing that some regions with harsh winter may even stop their service during this period (Figure 9).

Nonetheless, overall cold climate does not imply forcedly into small BSS usage since countries with cold winters such as Netherlands, Denmark or Germany present high bicycle usage rates (IDAE, 2007). Still, the guide points out the influence of the daily aspect of climate, where particular rainy, windy or extreme temperatures can decrease demand.

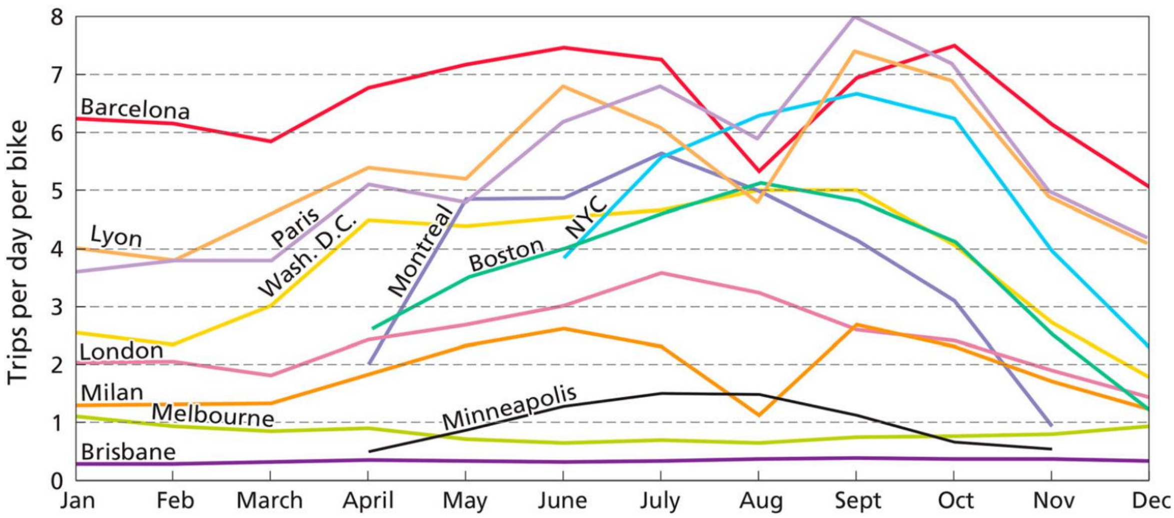


Figure 9 – BSS usage trips per day per bike, 2013.

Source: Fishman (2015).

2.4.2.6 Economic factors and financial situation

Economic factors may include costs such as wages, interest rates, governmental activity, laws, policies, tax rates and they heavily influence the value of an investment in the future. The city wealth and financial situation affect the amount of resources that may be available to a BSS, impacting its size, quality of infrastructure and degree of subside.

On the user's perspective, the final price matters and trip costs are usually lower than of other public transportation modes, like the bus (IDAE, 2007). To capture the user wiliness to pay, it is recommended to do pricing elasticity analysis to the different segments of the population affected (ITDP, 2013). These numbers communicate with the user Value of Time (VoT), defined as the monetary cost for one user that spends one hour of his/her time in the system (Badia, 2016) and a critical parameter to transportation studies (Brito and Strambi, 2007). It can be accessed through Stated of Revealed Preferences (SP / RP), where the last is preferable whenever possible. The VoT is less than wages in most studies although the relation is not linear and income elasticities vary between 0,3 and 0,7 depending on the purpose of travel (Bliemer et al., 2016).

Although there could be an impression that these economic factors would affect registration price, no evidence was found to support such assumption (Figure 10). It seems that BSS objectives surpasses a more direct correlation of city wealth and system accessibility, as is the case of Paris, a wealth city with a relatively affordable system with goals "*Improve mobility for all [...] Encourage economic vitality*".

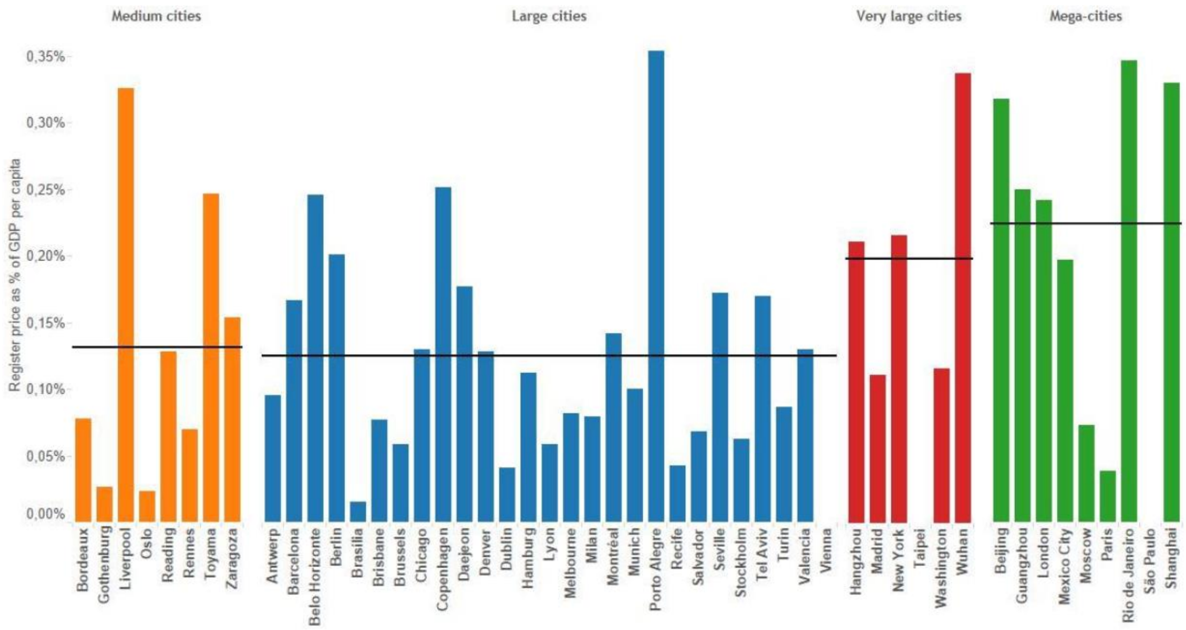


Figure 10 - Register price per GPD per capita by city-size clusters.

Source: Vassimon (2015).

Even so, it is comprehensible that cities and regions with a higher economic power can afford a better LoS and therefore a more expensive BSS design. For instance, in Switzerland, the average density of stations and number of bikes per inhabitant are relatively high compared to other contexts (Audikana et al., 2017). This happens even though having relatively low bike usage, which gives strength to the argument that richer regions can afford better systems.

2.4.2.7 Mobility behavior & Existing infrastructure

A cycling culture is quoted by several authors as a relevant factor for BSS (Department for City Planning New York, 2009; IDAE, 2007; ITDP, 2013; OBIS, 2011; Ricci, 2015; Transport Canada, 2009). But the other way around is also valid. The beginning of a BSS may be a catalyst for the everyday mobility with a bicycle and a first step so it can be seen in as a transportation mode where this is not common (IDAE, 2007). As an example, OBIS (2011) highlights Paris' case that had not the bicycle as this 'everyday' commuting purpose.

An enhancer for foment this culture is to create an adequate infrastructure, allowing easy and direct trips and safe travels in a usually dangerous environment (Médard de Chardon et al., 2017; Midgley, 2011; Ricci, 2015). Bicycle lanes cover both aspects. On the former point, it allows a straight path, usually connected in a network. On the last, it segregates bicycles from other transportation modes, with different speed and mass, which could be harmful to cyclists. It is seen the most BSS have such networks or had them implemented along the installation of the system (Midgley, 2011).

2.4.2.8 Demand

Although demand appraisal is not part of this work for its extension and complexity, a system demand is the spinal cord of any transportation mode. As such, it is important knowing where it comes from and relevant aspects that drives it. The above listed items are a summary of these multiple factors that affect it and try to explain its composition.

A reason for not extending the appraisal topic is also an alternative way of facing it from a transport supplier point of view. Demand can be seen either as an exogenous factor that responds to the chosen endogenous factors – the transport supply management – or seen as a target to be achieved. If the system is well designed, it is not a question of *if* the demand will be achieved, but rather *when* (Daganzo, 2010). The author goes further: an optimal design for a certain demand results in near-optimal solutions for a broad range of demands (within a factor of 2). He concludes, if demand does not change quickly, a well-designed system will present near optimal results for a long period of time.

With that in mind, one can go further in a qualitative point of view for grasping the demand of a region through other factors, mostly related to land use, that complement the ones already mentioned.

<u>Decide a coverage area</u> – a contiguous area in which bike-share stations are located added by a 500 m radius around each station located on the edge of the area (ITDP, 2013). Population come as a result of density in the region.

<u>Place it in the center</u> – as a general rule a city may deploy a BSS in a metropolitan core, where the population and job densities are the highest, if no mobility study was conducted (Midgley, 2011). The author caveats that more accurate demand projections are needed as the system gets embedded in the urban transport system.

Demand profile – it is relevant to check existing demand and conditions for cycling for the population in the designed area, the number of commuters, current modal split, existing transit, bicycle and pedestrian networks (ITDP, 2013). These number may also change when policies are changed during the system operation, as when London saw a new demand pattern arise after a change in policy allowing casual users (Ricci, 2015).

Demand as an Uptake rate – a simple methodology is to use a range of market penetration that would use a service. An example is New York City BSS study, which used 3, 6 and 9 percent of the city's population for the financial estimations (Department for City Planning New York, 2009). The real number will depend of the numerous exogenous factors as well as the endogenous factors decided during the planning.

Demand studies – demand can be estimated through a Price-Elasticity of Demand from its various customer types (ITDP, 2013). Note that this is a more elaborate way than the uptake rate.

Midgley (2011) on his analysis concludes that it is not too early to seek new ways to develop robust and simple methodologies to achieve demand levels that are accurate enough for the planning purposes.

Truth be told, it is not an evident task to assign the system design to cities as if there was one major determinant that overlapped others. Cities have their own dynamics that end up affecting greatly the transportation network and system use (Figure 11). So, it is up to city and transport planners to provide useful tools to decision makers.

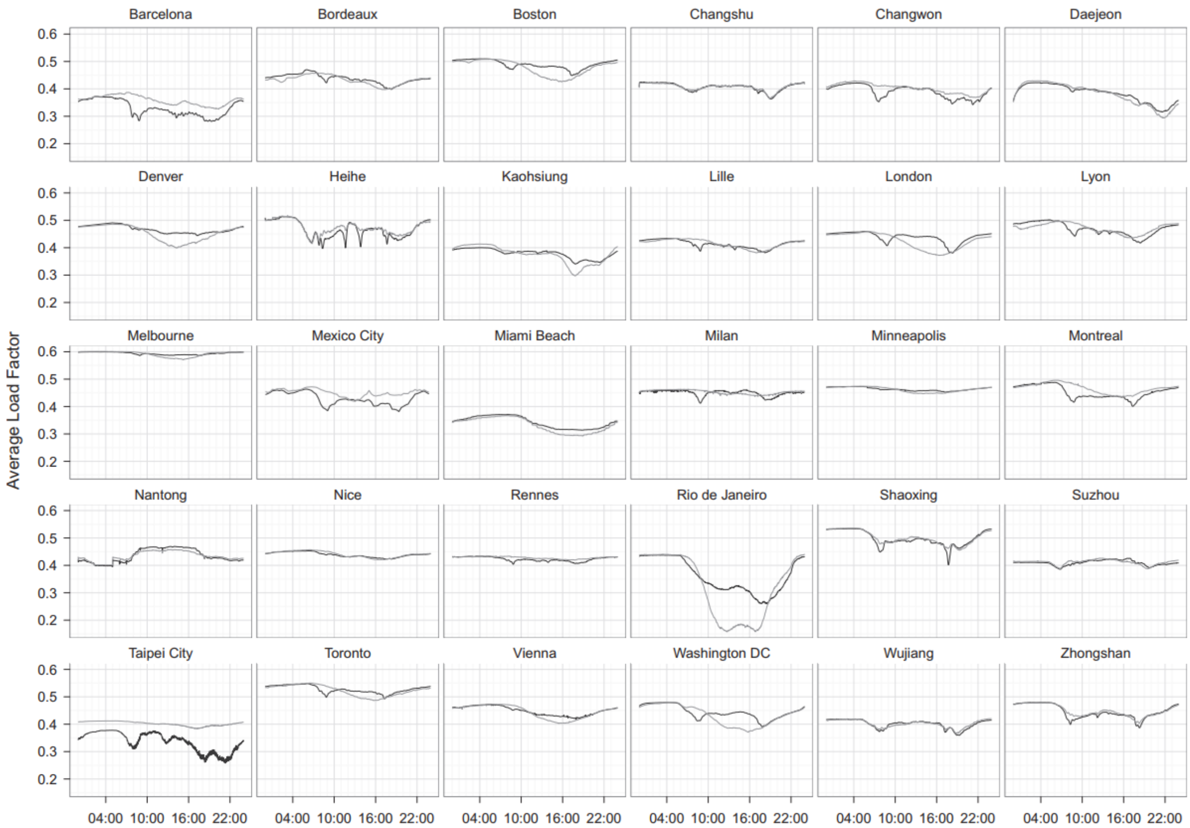


Figure 11 - Load factor variation for weekdays (black lines) and weekend days (grey lines).

Source: O'Brien et al. (2014).

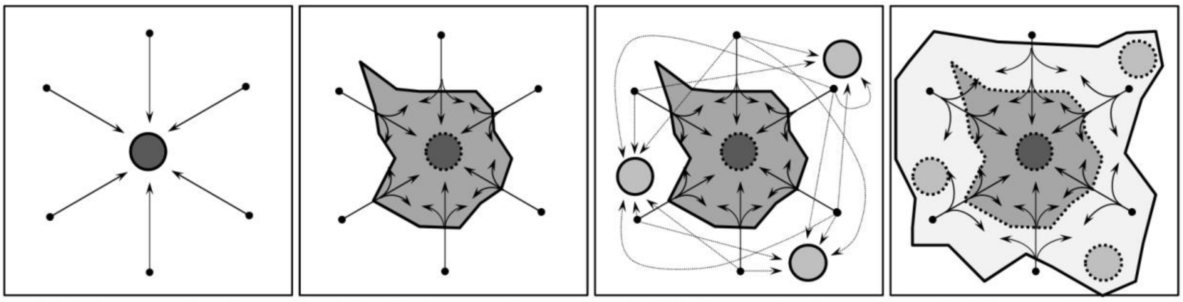
2.5 Centrality

2.5.1 Urban structure

The urban spatial structure from cities evolved from initial centralized scenarios to more dispersed ones (Figure 12). They come from a pre-industrial phase with a very centralized activities in the Central Business District (CBD); to a more scattered one in where activities take place around the CDB in an industrial phase; and finally to a more dispersed form in contemporary times (Rodrigue et al., 2016).

Even with this dispersion with multiple clusters, the CBD remains the most relevant among them, which characterized the mono-polycentric model used by Badia (2016). The author indicates that the higher modal splits of transit system gave a monocentric urban structure to European cities, what did not happen to the American counterparts which present a more dispersed structure.

The identification of this center is important. As seen before, the CBD concentrates demand and demand decreases when it far away from it (Ricci, 2015). The reason for it are the high employment densities and rich retail, public facilities and entertainment services (Transport Canada, 2009).



(a) Monocentric city, centralization and concentration

(b) CBD extension, Deconcentration - and low decentralization

(c) Polycentric city, decentralization - and low deconcentration

(d) Dispersed city, decentralization and deconcentration

Figure 12 - Urban form evolution and mobility patterns associated.

Source: Badia (2016).

This characteristic affects the BSS mainly in two different ways. The first is that demand on a peripheric region is lower and design decisions would affect a smaller number of people than they would to this central region. For that reason, it is worth to question until what extent is worth to expand a system and if the decision is made, what LoS are to be asked from the operator.

The second is that flow patterns will be different and respond to this centric attraction with an unbalance. This is evident mostly during the morning peak, but its weight can still be felt during other periods of the day.

2.5.2 Higher demand in central regions

Martinez et al., (2012) in his Lisbon's BSS study analyzed the spatial and temporal variability where both factors can be seen (Figure 13). The centric region which accounts for approximately less than half the BSS area presented a much higher demand than the peripheric area. The first had averages above of 300 daily trips within its region while the peripheric parts had around 100. On the same picture it can also be seen the predominant flows in different time periods. The central region attracts a good part of the flows generating an unbalance in the system. The exception is the night period, which presents a sprawled demand.

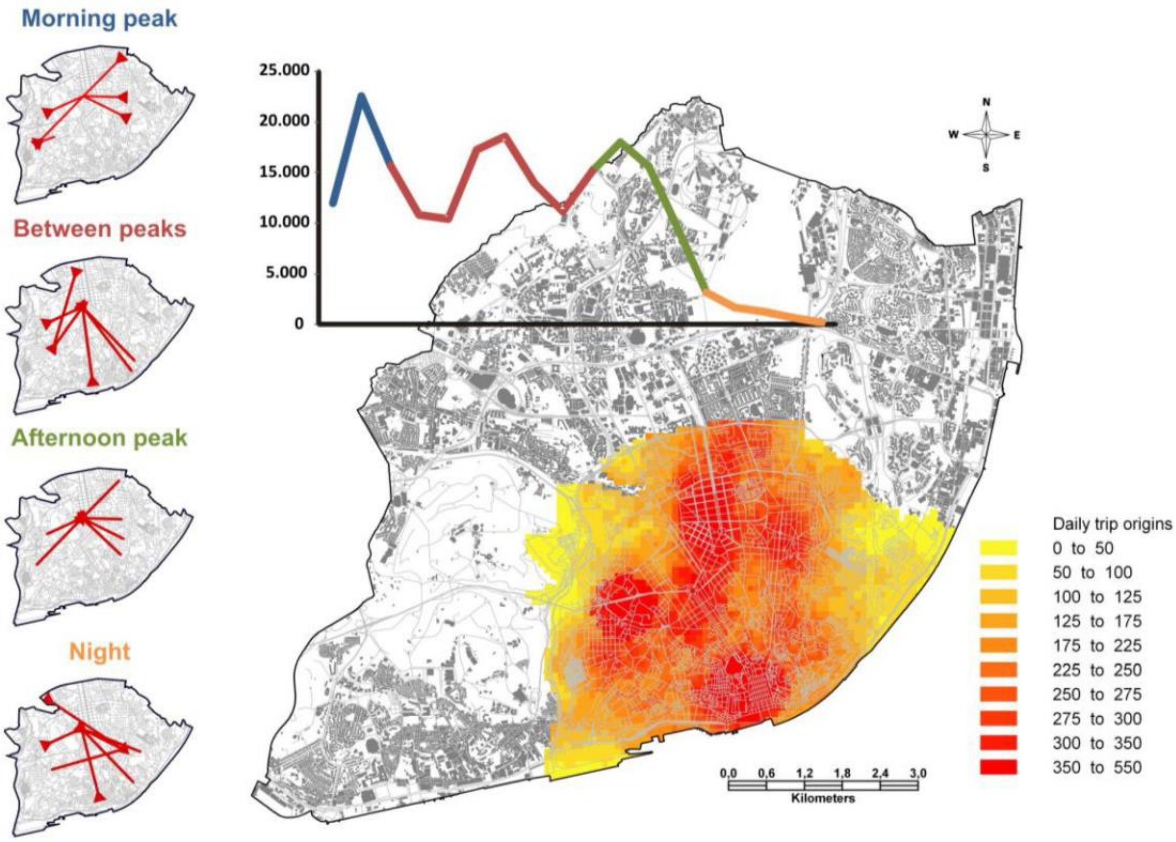


Figure 13 - Spatial and temporal distribution of demand of Lisbon's BSS.

Source: Martinez et al. (2012).

A higher demand is usually desired, since a BSS gains purpose as bicycles are used multiple times during the day. One problem could occur if there is an imbalance, which means that one region operates more as an attract or destination point. The CDB's dynamic enhances this multiple use and it is expected smaller operational costs within a region. Figure 14 illustrates this effect in Barcelona's BSS, where there is a central region of higher demand which reasonably coincides with its CDB and the region of smaller operational costs for trips. Although the topography is relevant, leading to higher costs in high elevation areas (the north of the image), within a same elevation trip costs go up on the system borders. Savings due to economy of scale for having a higher demand, and additional cost for the longer distance and unbalance could help to explain this effect.

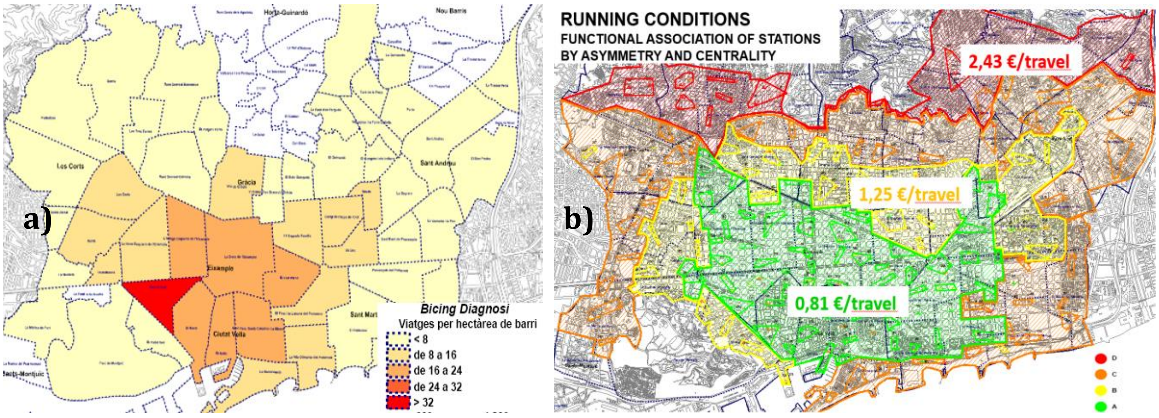


Figure 14 – Barcelona's BSS a) Demand and b) Trip costs.

Source: Adapted from Lopez (2009)

2.5.3 Center-periphery unbalance

The center-periphery unbalance occurs when the central region attracts more demand than generates (or *vice-versa*) for its characteristics of lower population density. It may be steady during the day, with a clear pattern of attraction, or change according the time period, i.e., attract during the morning and generate during the afternoon.

NYC's BSS Citi Bike presents predominantly the second type with unbalances in marked time periods (Figure 15). Although not geographically accurate, if one considers Manhattan as the centric region and the Brooklyn and Queens regions the periphery, the flows between them are marked as morning attraction to Manhattan and the reverse during the afternoon. It is curious to see the proportions also, a 3 to 1 unbalance, meaning that during the morning approximately ¾ of trips between regions are towards Manhattan.

Schneider (2016) goes further and quantifies what it represents on the total demand, with an overall breakdown of 88% of trips starting and ending in Manhattan; 8% of trips starting and ending in an outer borough; and 4% of trips travel between Manhattan and an outer borough.

Considering the daily 48.000 trips analyzed by the author, the 4% trips between regions result in a total 1920 trips that need to be rebalanced during the day. As a rough estimation, supposing a 18 h working day, that one van carries 30 bicycles and takes one hour and a half to do a tour trip (since the distances are over 10 km), it would mean 6 vans are needed exclusively to deal with this unbalance.

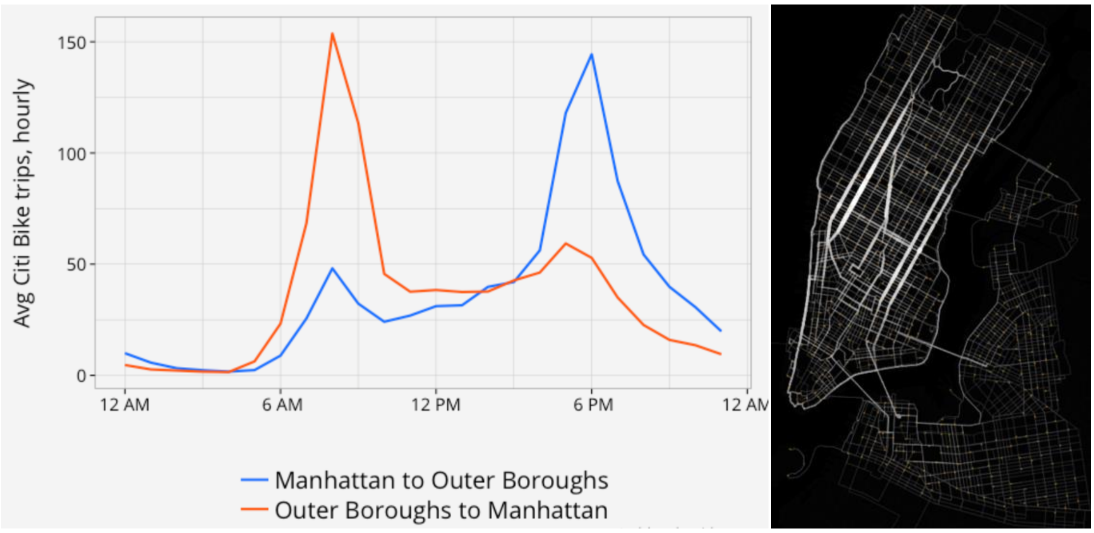


Figure 15 – Centrality unbalance in NY BSS.

Source: Adapted from Schneider (2016).

The Citi Bike expanded in 2015, mostly to outer boroughs and the upper Manhattan Island (Figure 16). It is possible to imagine that these numbers were different before the second phase as well as the distances smaller.

During the initial design or when planning expansions, it may be important to have this factor into consideration. The further one goes from one central region (without merging with a new CDB), chances are the average region demand will be smaller and the unbalances higher.

Here comes an important conflict for politicians to decide. On one hand, expanding the service will probably mean higher expenses and not proportionally to demand (benefiting a few more people for a much higher cost). On the other, commonly the Medium Household Income (MHI) is lower in the outskirts of a city which means that providing this service will also results in providing equity and the *right to the city* for the less fortunate (Figure 17). Finding the correct balance between both is the challenge.

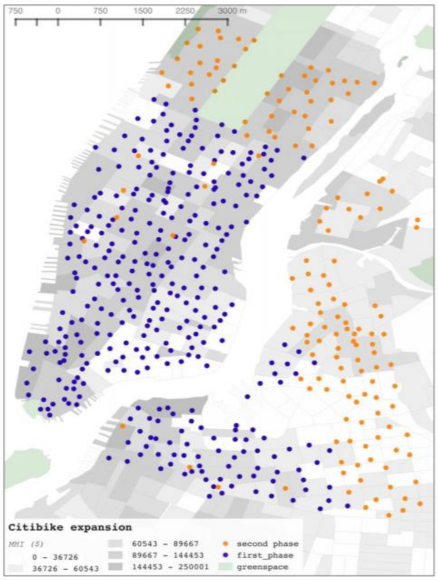


Figure 16 – Citi Bike first and second phase of station installations.

Source: Tedeschi (2016).

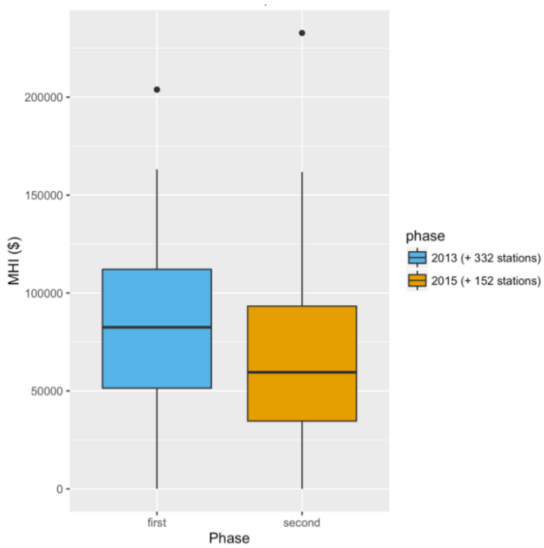


Figure 17 – MHI boxplot for first and second phase census tracts of Citi Bike.

Source: Tedeschi (2016).

2.6 Barcelona's BSS - Bicing

The city of Barcelona has an area of 102 km^2, divided in 10 neighborhoods and 73 districts and an average population density of 16 thousand inhabitants / km^2 with around 1,6 mi inhabitants (Figure 18). Barcelona's BSS system is called Bicing, its origin dates from 2007 and is the largest BSS in Spain. The service is located in an area of 50 km^2 (on 51 districts), with 420 stations (20 of them electric). This will result in an average 8 station / km^2.

The city has a marked topography outline due to the presence of the sea and the mountains. This causes significant difference between the sea level (0 m) and the neighborhood hills (with over 400 m) (Figure 19). As a consequence, Bicing users manifest a preference for not making the uphill trips sometimes (35 %) or never (7 %) (Figure 20).

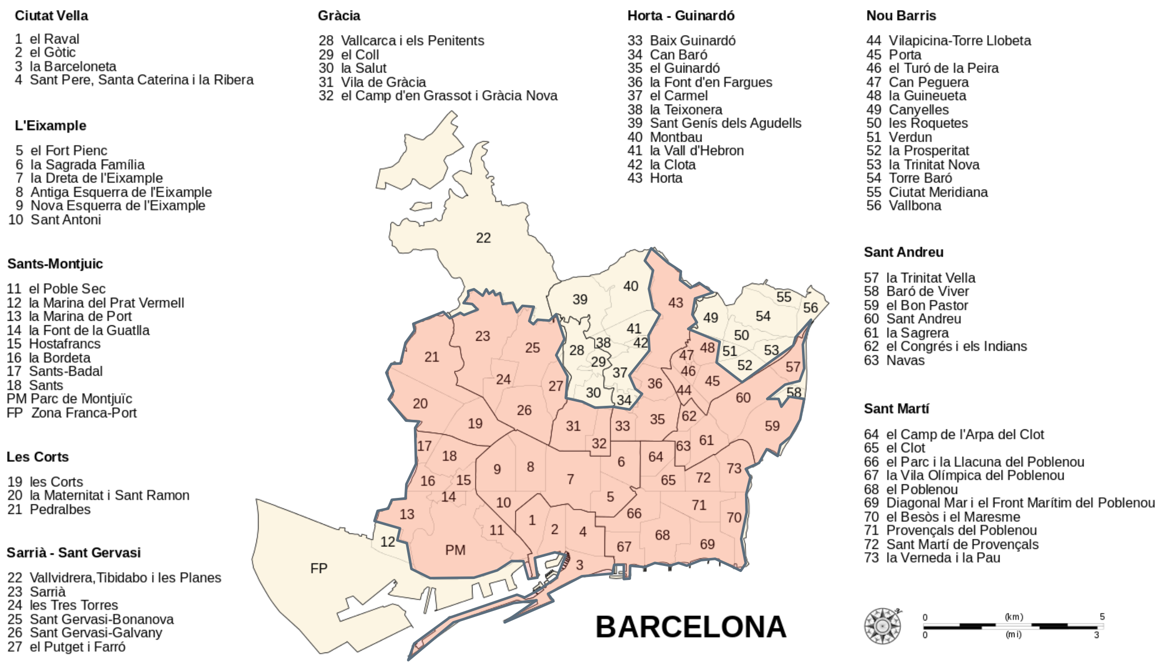


Figure 18 - Barcelona neighborhoods and districts (in red the ones with stations).

Source: https://es.wikipedia.org/wiki/Distritos_de_Barcelona

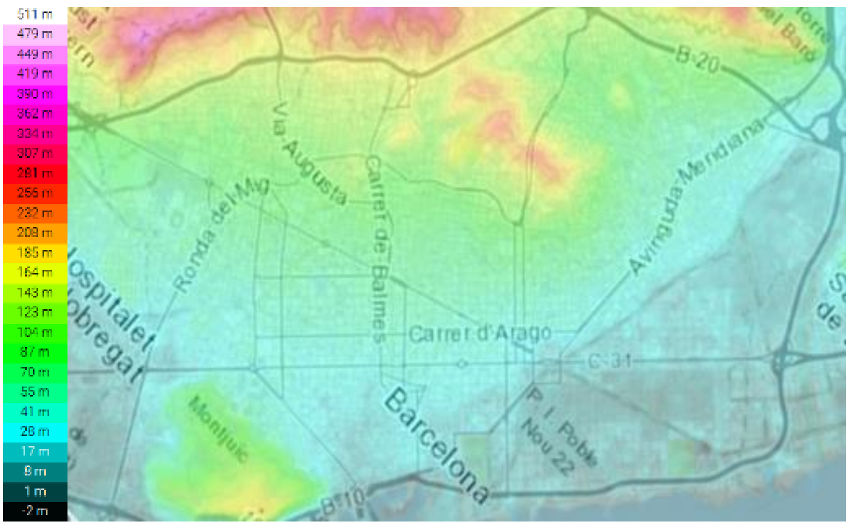


Figure 19 – Barcelona topography.

Source: http://pt-br.topographic-map.com/places/Barcelona-8994740/

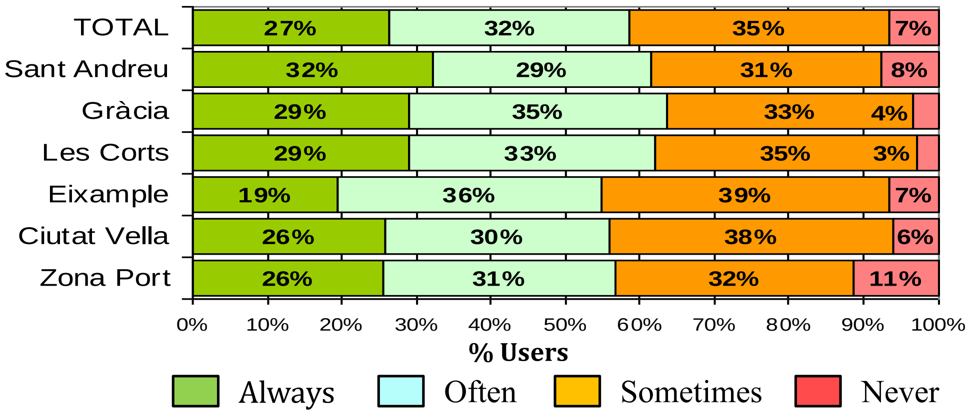


Figure 20 - Wiliness to uphill trips according to starting neighborhood.

Source: (AAD Market, 2007).

Service levels vary considerably along the day since demand changes and peaks during marked hours. For instance, Llopis (2016) found in her study in Bicing an average of 19 % of the stations being full or empty (No-Service). It is worthy also to differentiate both. They have different natures and present different numbers most of time, with the empty ones being always bigger than the full ones, as seen in Figure 21, with 40 empty and 9 full stations.

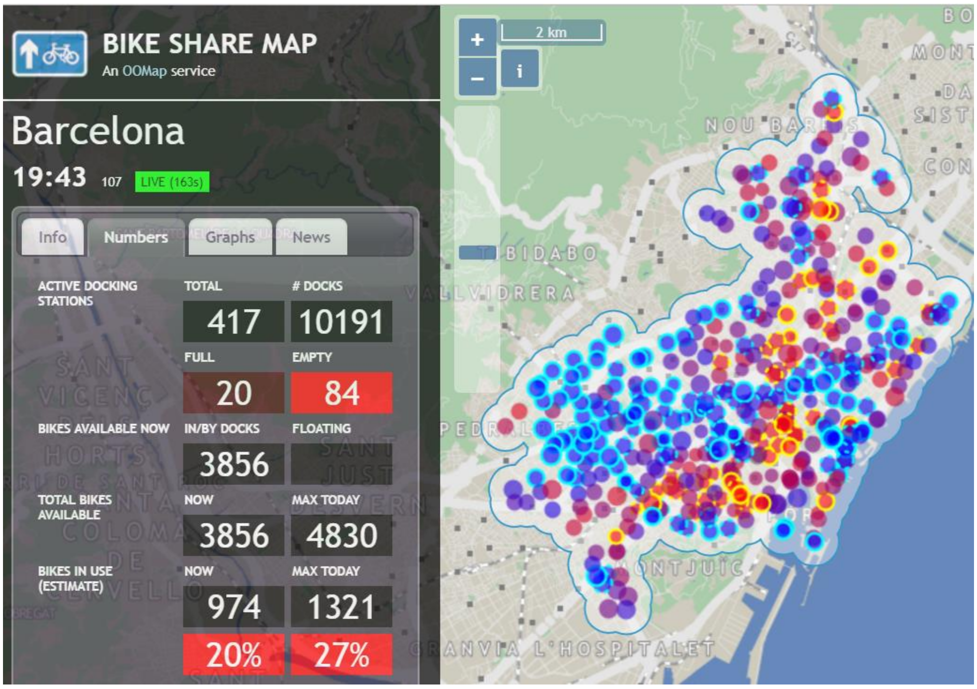


Figure 21 – Bicing station occupancy.

Source: http://bikes.oobrien.com/barcelona/

It may also be relevant to differentiate them according to the centrality of the system due to the demand differences between regions. This means that a worst LoS in the center would affect more people and, at the same time, having a better LoS in a distance zone could be too expensive.

Public body and operators must be aware of such numbers during their planning. For instance, Barcelona City Hall established different acceptance levels of No-Service for empty and full stations according to the centrality each region had. When writing its bidding process for the new Bicing 2.0 (valid for the 2018-2028 period) the numbers were progressively bigger for empty stations, with a tolerance 2,5 times higher in the periphery than in the center (Table 14). Although this can be seen as segregationist, the option could be paying much more for the operators or even not to have a service at all in these zones.

Curiously enough, the full station tolerance in the bidding has a smaller tolerance between zones and it is even more tolerant in the central area. Although no reasons are presented in the document for such choice, one possibility could be the acceptance of a naturally high inflow to central areas and the fact that it is easier to manage full and concentrated stations than empty ones.

Table 14 – No Service tolerances for each zone in the new Bicing bidding.

Zones	Empty	Full
Ring 1	7,0 %	5,0 %
Ring 2	8,0 %	3,0 %
Ring 3	18,0 %	3,0 %

Source: Gerència Ajunta de Mobilitat i Infraestructures (2016).

3 Methodology

The following chapter proposes the methodology of setting a BSS to capture the systems main parameters and be adaptable to the most common scenarios where the system is needed.

The model includes a region that one entity (public or private) is considering to implement a BSS. How much would it cost for the Operator? How many bicycles are needed? Stations? Vans? Will the User walk a lot? These are questions that the model tries to address.

This model describes an BSS with analytical equations. It assumes continuous approximations in order to simplify reality, considering the main decision variables (DV) and parameters. These decision variables need to be established by the agency in the implementation or expansion of the system. The parameters depend on the system context and conditions and are fixed for a given scenario (or a set of them).

The modeling starts with some basic inputs that characterize BSS, their environment, users and parameters. This model is based on a center-periphery region differentiation. It is highlighted also the inputs of most interest, that are the core of the adaptability of this model for they allow new scenarios that reflect very different cities profiles.

The model itself is composed of equations that capture the costs of main stakeholders: the user and the agency. The User cost considers the access cost and the LoS while for the agency the infrastructure, the repositioning and the general operational costs.

Finally, through optimization station density, number of bikes and agency yearly cost come as important outputs. The proposition scheme is summarized on Figure 22.

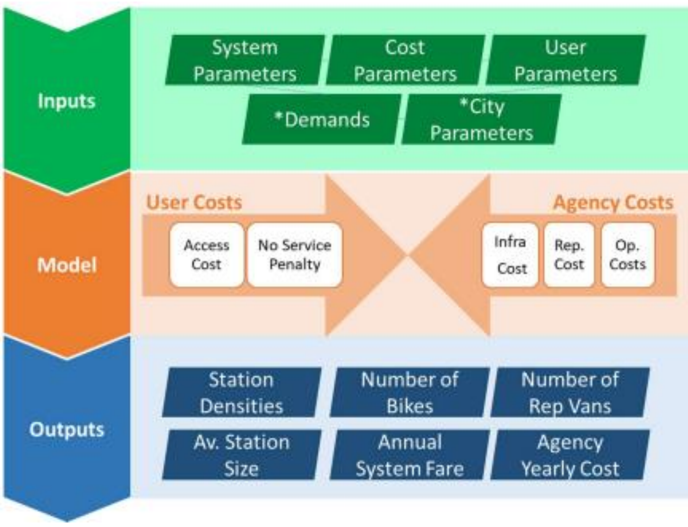


Figure 22 - Modeling approach resume.

3.1 Setting the system

The project proposes a generic city with a region of area $\boldsymbol{R}$ (km^2) where the BSS is, having a center area of $\boldsymbol{\varphi.R}$ (km^2), with a high centric bicycle-request demand density $\boldsymbol{\lambda_c}$ ($trip/h.km^2$). This region has a periphery $\boldsymbol{(1-\varphi).R}$ (km^2), with a lower demand density $\boldsymbol{\lambda_p}$ ($trip/h.km^2$). The net difference in users going mostly towards the center (or the other way around), creates an unbalance $\boldsymbol{P(c)}$ (%). The region also presents an averaged slope $\boldsymbol{\alpha}$ (%) which will imply in $\boldsymbol{P(\alpha)}$ (%) lost trips from users not willing to go uphill. In other words, roughly half the zone is below the average elevation ($z < 0$), which will receive return trips as a net unbalance and half above ($z > 0$), which generate request trips.

From these inputs, the BSS will have Decision Variables that affect both User and Agency: Station Density $\boldsymbol{\Delta_{c/p}}$ ($st./km^2$) in the **c**entre (c) or **p**eriphery (p), a probability of having full or empty stations $\mathbf{P_{e/f\text{-}c/p}}$ (%) and an Rebalancing Period $\boldsymbol{h}$ (hours) in which vans set the system back to balance so users can have a determined LoS (Figure 23).

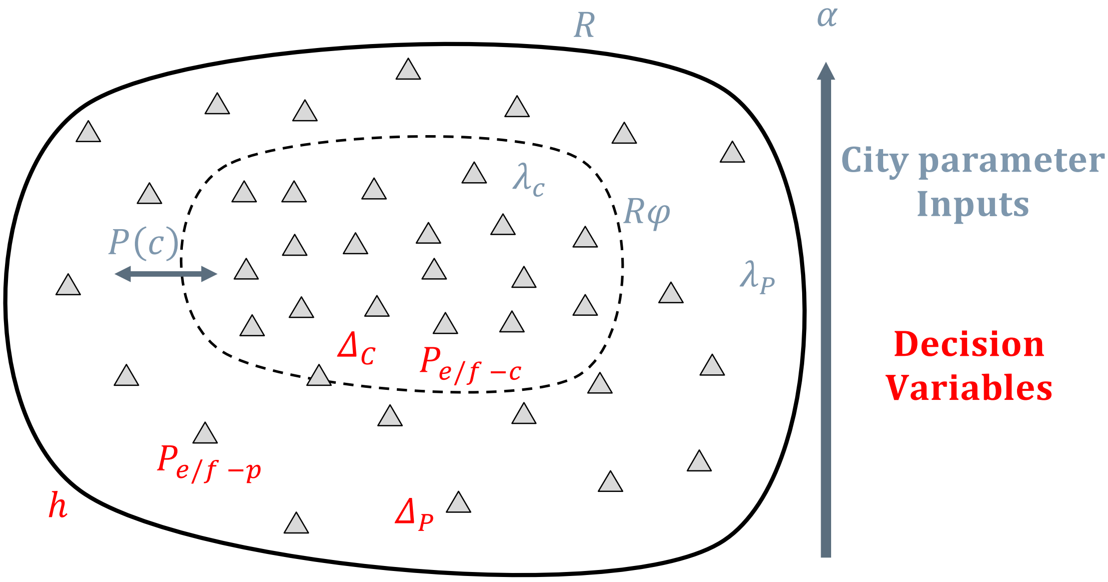


Figure 23 - Schematic representation of the system and its Decision Variables.

Regarding the level of demand and its spatial distribution, all analytical models assume some simplifications of the reality. Since the idea is trying to propose a model that can be used on regions with no initial data, demand is simplified without considering time variations, λ (p/h) represents the average hourly demand of the service system. It is excluded from this analysis then a possible average demand within a period h: λ_h (p/h); and the demand at rush hour: Λ (p/h). These values are supposed to be constant and do not vary with the level of service or other factors related to the service supply.

3.2 Monocentric approach

The city center is a place of higher demand and that can present a center-periphery unbalance. To find this centric region the first step proposed is to locate a ground-zero, or in other words, the center coordinates where this centric region can be investigated.

For have this initial location, some suggestions are proposed that come from relevant aspects that drive demand from the literature and are relatively easy to find: the total population and the jobs/offices (and/or their densities) from each region. The physical center of a region is also an easy-to-get data that plays a role in this simple proposal for its geometrical distribution that could provide equity and accessibility to less favored regions. There is no reason why these coordinates should coincide but even so, they create an area of possibilities that are options for the model ground-zero (Figure 24).

In addition, the exact position could be weighted by other objective factors or be selected by deeper knowledge of the city and the mobility behaviors. For example, a touristic and old city center could also be comprehended in the feasibility factors even if there are not as much offices and population that would justify its consideration. In any case, it is expected that the proposed coordinates from this method are rather close together in comparison with the city's dimensions.

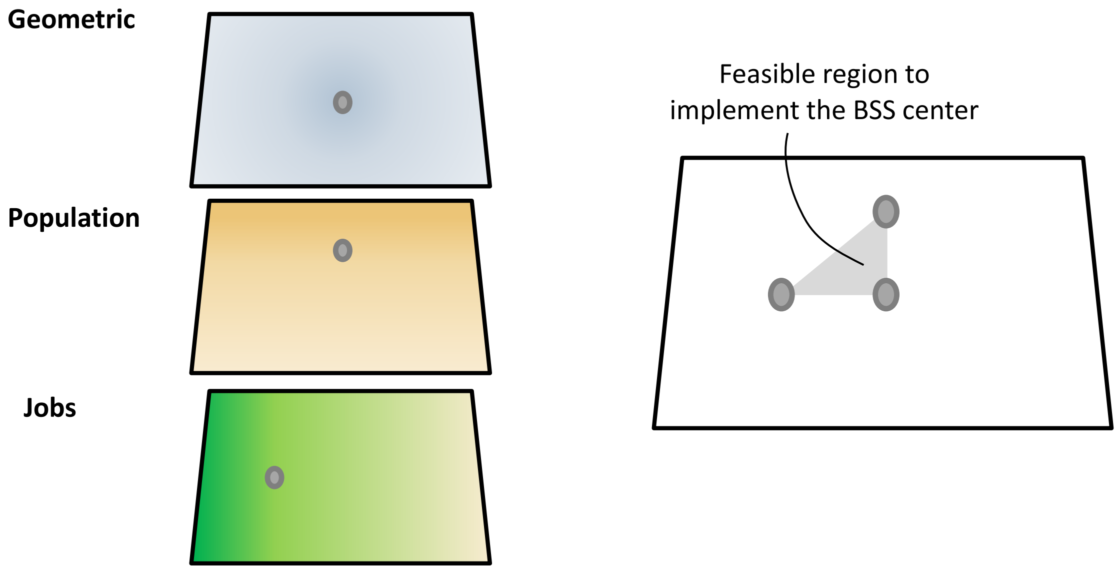


Figure 24 – Exploration of a feasibility zone for a BSS center.

Nevertheless, not every region may have the characteristics that allow this centric definition. This approach does not apply when there are multiple centers (maybe from a new emerging business district), where one city dimension is much bigger than the second (usually due to topography), the population distribution is too heterogeneous or the topographic elevation is so high in the city center could mean that this approach is not adequate (Figure 25).

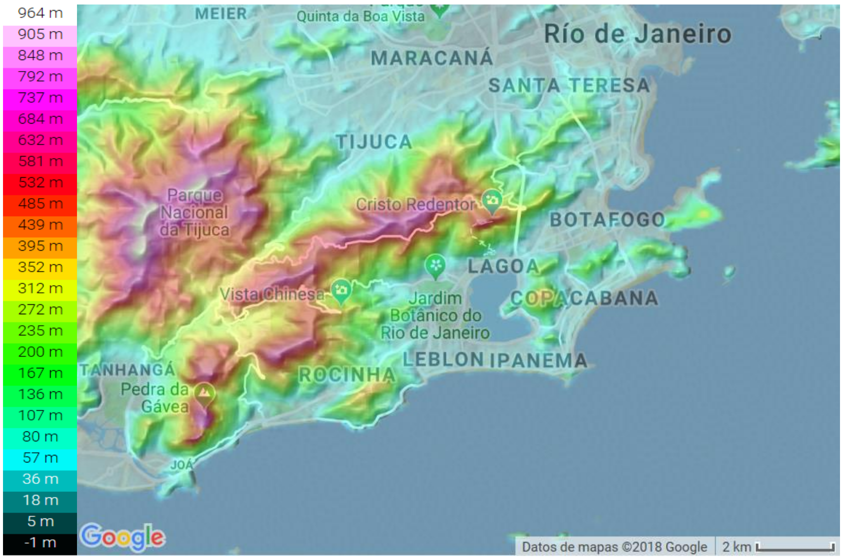


Figure 25 - Non-centric regions - Squeezed region between mountains.

Source: http://pt-br.topographic-map.com/

Once defined a centric point, it is important to determine the centric region that presents concentrated activity with higher demand. Starting by the easiest way, if there is a BSS already present, it is enough to check demand on each district by its proximity with the central point. When there is an abrupt change in the demand pattern, one could cut and set the region as the center-periphery limit (Figure 26).

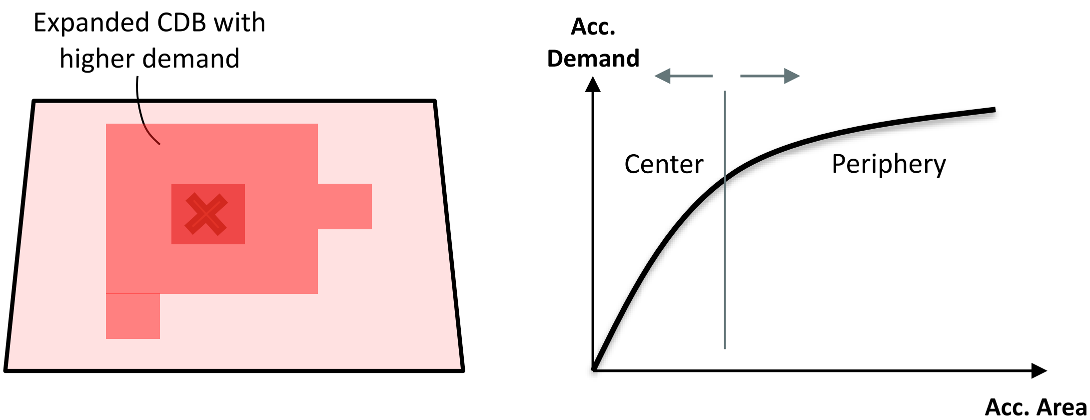


Figure 26 - Center definition proposal.

If it is an exploratory region for a new system, there are still a few options. Under the same strategy of exploring the adjacent districts, one could search for the jobs density, office areas, number of commerce or any available data that could indicate an approximate CDB. The expectation is the same. At some point the further regions will present such a descent on economic related activities that it will be possible to « draw a line ». An alternative from this idea is to experiment with the population density which usually gets less dense away from the city.

Bear in mind that these are not exact methods, nor is it clear where to separate regions. Nevertheless, the whole idea is to explore and propose an initial design that can be backed up for the city specificities. With it, no region identified will be equal to other, from another city. Also, inaccuracy from this method is expected to be within the natural threshold that a continuum approximation will always have. And finally, on a detailing phase or even on the system implementation, regions adjustments can be done without incurring heavy costs, for the design shall be robust and change only in specific – and small – regions.

3.3 Costs

The project proposes an optimization of a Generalized Cost Function that leads to a system design that balances the trade-offs between User and Agency. For that, each cost incurred directly or indirectly through the specifications of the system is weighted between these two stakeholders. One example is the system station density DV $\boldsymbol{\Delta_{c/p}}$ (how many stations there are in one square kilometer). On one hand, users benefit greatly from a ubiquitous system where stations are very easily found (Chart 2). On the other hand, agency has its major cost on station acquisition and installation, which would lead to have them more scattered in a region than most users would desire.

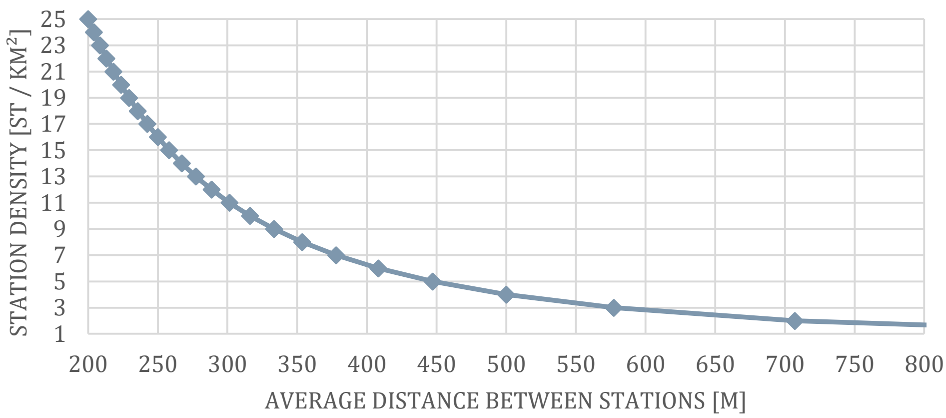


Chart 2 – Relation between station density and their average distance.

The model is one optimization of Users Cost and Agency Cost. The former considers Access to the system and No-Service-Probability (NSP), the possibility of finding an empty full station when needed. The Agency Costs account Rebalancing (i.e. bringing bicycles with vans where they are needed), Infrastructure (i.e. acquisition and maintenance of bicycles and stations), and Operational Costs (e.g. maintenance, customer services, overheads) (Eq. 1):

$$[\mathbf{min}]\ \mathbf{Z} = \overbrace{\mathbf{Z_A} + \mathbf{Z_{NSP}}}^{\textbf{User}} + \overbrace{\mathbf{Z_R} + \mathbf{Z_I} + \mathbf{Z_O}}^{\textbf{Agency}} \left[\frac{\boldsymbol{€}}{\boldsymbol{h}}\right]$$

Eq. 1 – General Cost Function

The decision variables have the following constrains, mostly defined by examples or logic:

- $2 \leq \boldsymbol{\Lambda}_{\mathrm{c;p}} \leq 25$ – Numbers are found on operating BSS. The lower constrain is mostly common on peripheric regions of low population dense cities. The upper is superior to Bicing densest station district (with 20 st./km^2) and results in an average access distance of 100 m, a rather small number. Further increasing it would mean little to diminish this distance.
- $0{,}01 \leq \boldsymbol{P_e}, \boldsymbol{P_f} \leq 0{,}33$ – A one percent is due to the feasibility of maintaining very low LoS, while the highest threshold is an arbitrary reference, but reflects a system with a poor LoS.
- $\boldsymbol{P_f} \leq 2 \cdot \boldsymbol{P_e}$ – It is more common the occurrence of empty than full stations.
- $3 \leq \boldsymbol{h} \leq 24$ – A lower than 3 hours repositioning time would most likely affect the hypothesis that this period unbalancing would not affect demand. The 24 h period considers that there is no reason for this not be performed during one whole day.

Optional constrains that can help decision makers are:

- Annual Operation $\leq$ Budget – Set a maximum budget available to run the system
- Standardized optimization – If one set DV is desired and the others want to be explored (e.g. having a set P from a contract and determining which station density and rebalancing period is optimal).
- Space restriction – For very high demand densities, good LoS and/or when holding the station density DV, it can happen very large station solutions (with over 40 slots on average). It can be interesting to constrain it if the city is not willing to dispose of so much space for the BSS. Also, it helps the upcoming hypothesis that stations have one single price, no matter their size.

The main hypothesis that drive the model in general terms are:

- Demand homogeneity within a region – demand is considered homogeneous or with differentiations that can be neglected in terms of system design outputs.
- Center-periphery demand heterogeneity – differences between regions are sufficiently marked that they should be differentiated. This is a balance between realistic models, much more complex, and a completely homogenous model. Also, results on the system configuration are not so significant if the goal is obtaining general insights (Badia, 2016).
- Static demand – demand does not change in time. Although it does not capture realistically urban spatial process, the approach is used to this day as a simplified mean to add a land use dimension to existing transport models or because the static model represents an equilibrium state which is of interest in itself (Sivakumar, 2007).

The more specific ones, that explain one particular equation, are displayed as the modeling methodology is unraveled.

3.3.1 Access Cost

Let us address each term. The Access Cost from a User perspective is set by the distance each user has to walk ($dist_{C/P}$) from each region, center or periphery. Multiplying it by the demand ($\lambda_{C/P}$) from region area (R) and dividing it by a person walking speed (v_W) leads to the time spent walking time from and to a station by all users (Eq. 2). Considering a Value of Time (β) [€/h] it is possible to access the hourly cost of accessing and egressing the system:

$$\boldsymbol{Z_A = \frac{\beta \cdot R}{v_w} \cdot \left(dist_p \cdot \lambda_p \cdot (1-\varphi) + dist_c \cdot \lambda_c \cdot \varphi \right) \left[\frac{€}{h}\right]}$$

Eq. 2 – User Access Cost.

The average distance walked by a person to access (or egress) the system is function of the station density ($\boldsymbol{\Delta_{C/P}}$) and whether or not its destination is to a central region (f_C), with a higher station density, or periphery (f_P) with a smaller one (Eq. 3). The average distance walked corresponds to the influence area of one station $1/\sqrt{\Delta}$ divided by 2 due to the L1 metric (Figure 27). Although the square lattice is not the best disposition for stations, this overestimation in walking distance could compensate possible unbalances caused by the current practice of multiple stations that are so close together that they can be considered just one.

$$Av.walk = \frac{1}{4} \cdot \frac{1}{\sqrt{\Delta}} + \frac{1}{4} \cdot \frac{1}{\sqrt{\Delta}} = \frac{1}{2\sqrt{\Delta}}$$

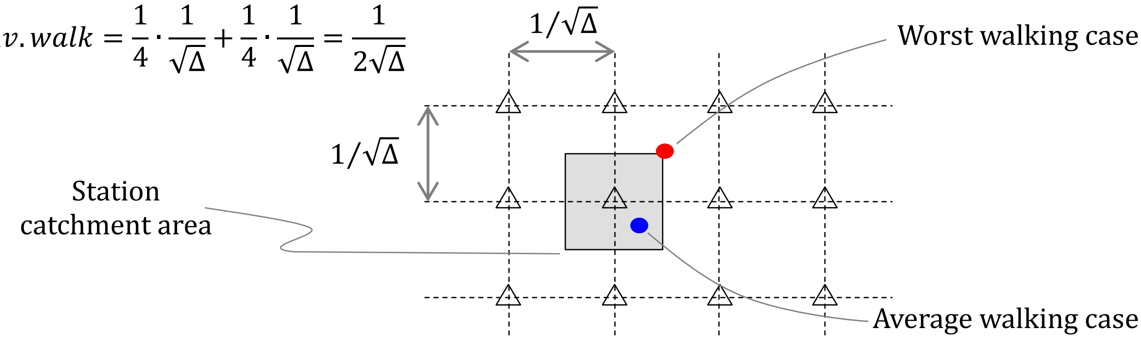


Figure 27 – Average walking distance for a user.

$$dist_p = \frac{1}{2} \cdot \left(\overbrace{\frac{1}{\sqrt{\boldsymbol{\Delta_p}}}}^{Origin} + \overbrace{\frac{f_p}{\sqrt{\boldsymbol{\Delta_p}}} + \frac{1 - f_p}{\sqrt{\boldsymbol{\Delta_c}}}}^{Destination} \right); \; dist_c = \frac{1}{2} \cdot \left(\frac{1}{\sqrt{\boldsymbol{\Delta_c}}} + \frac{f_c}{\sqrt{\boldsymbol{\Delta_c}}} + \frac{1 - f_c}{\sqrt{\boldsymbol{\Delta_p}}} \right) \; [km]$$

Eq. 3 – Distanced walked by users to access and egress the system.

The f_c and f_p factors allow a simple, but necessary, origin and destination matrix (Table 15). They correspond to the fraction of the demand originated that has a destination for the same region. This is important for accounting the differences of walking distance for these different users and will later make possible to quantify the unbalance between regions (Eq. 4). If there are more trips to the center, the unbalance factor P(c) will be positive. If most of the flow is towards the periphery, negative.

Table 15 – Origin and destination matrix for the system.

Origin \ Destination	Center	Periphery
Center	f_c	$1 - f_c$
Periphery	$1 - f_p$	f_p

$$P(c) \cdot \lambda = \overbrace{\left(1 - f_p\right) \cdot \lambda_p \cdot (1 - \varphi)}^{p \to c} - \overbrace{(1 - f_c) \cdot \lambda_c \cdot \varphi}^{c \to p}$$

Eq. 4 – Center-periphery unbalance.

The main assumptions for this section are:

- Users move in a L1 metric
- Users are always driven to the closest stations, even if their trip direction is opposed to its final direction (which in practice does not always occur).

3.3.2 No Service Penalty

No Service Penalty correlates the users cost in not finding a bicycle (or finding a full station) and having to go the next station (Eq. 5). In the worst case, it means even abandoning the system and trying other transportation modes. To access this cost, consider the Value of Lost Time (β_L) for accessing a new station - which is bigger than the VoT (β) - from every user within each sub region in R, where the decision variables $\mathbf{P_e}$ means the user closest station is empty or/and full at destination ($\mathbf{P_f}$). If the user comes/goes from or to the periphery or center makes a difference since, again, the station density will imply a larger moving period (Figure 28).

$$Z_{NSP} = \beta_L \cdot R \cdot [Lost\ Trips] \left[\frac{€}{\boldsymbol{h}}\right]$$

Eq. 5 – No Service Probability Cost.

This lost trip will imply in the user either trying to go to a next station or going to with another transportation mode (Eq. 6). The probability of one or the other are closely the same (AAD Market, 2007) and it will not be considered the option where users wait for a bicycle or slot. It is also considered a penalty of 10 minutes when the users choose to take the public transport since it is generally more scattered than a BSS station, implying in greater walking times, beside the waiting and possible transfers one shall incur. Also, it is not considered cases where the user could walk to a 3rd or more stations within a region since the factor would imply in probabilities P with cubic or higher factors, which are too small to have an impact on the result. Figure 28 illustrates the NSP applicability for users.

$$Lost\ Trips = \frac{\lambda_c \cdot \varphi}{2} \cdot$$

$$\left[\boldsymbol{P_{e-c}} \cdot \left(\overbrace{\frac{1}{2 \cdot \sqrt{\boldsymbol{\Delta_c}} \cdot v_w}}^{Walk\ to\ next\ st.} + \overbrace{\frac{PT_{FARE}}{\beta} + \frac{10}{60}}^{Pay\ a\ PT\ fare\ and\ wait}\right) + \overbrace{\frac{f_c \cdot \boldsymbol{P_{f-c}}}{\sqrt{\boldsymbol{\Delta_c}}} \cdot \left(\frac{1}{v_b} + \frac{1}{v_w}\right)}^{Ride\ to\ next\ central\ st.\&\ walk\ back} + \overbrace{\frac{(1-f_c) \cdot \boldsymbol{P_{f-p}}}{\sqrt{\boldsymbol{\Delta_p}}} \cdot \left(\frac{1}{v_b} + \frac{1}{v_w}\right)}^{Ride\ to\ next\ per.\ st.\ \&\ walk\ back}\right] +$$

$$\frac{\lambda_p \cdot (1-\varphi)}{2} \cdot \left[\boldsymbol{P_{e-p}} \cdot \left(\frac{1}{2 \cdot \sqrt{\boldsymbol{\Delta_p}} \cdot v_w} + \frac{PT_{FARE}}{\beta} + \frac{10}{60}\right) + \frac{f_p \cdot \boldsymbol{P_{f-p}}}{\sqrt{\boldsymbol{\Delta_p}}} \cdot \left(\frac{1}{v_b} + \frac{1}{v_w}\right) + \frac{(1-f_p) \cdot \boldsymbol{P_{f-c}}}{\sqrt{\boldsymbol{\Delta_c}}} \cdot \left(\frac{1}{v_b} + \frac{1}{v_w}\right)\right] \left[\frac{Trips}{km^2}\right]$$

Eq. 6 – Probability of Lost Time composition.

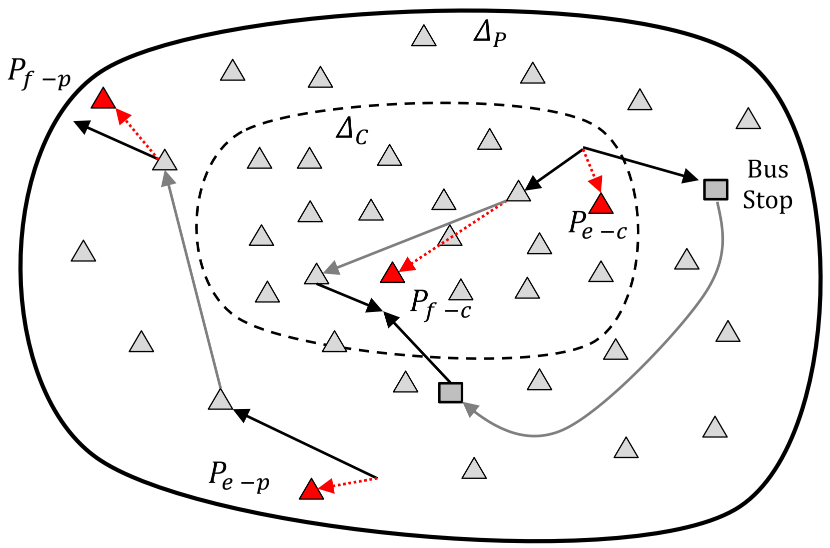


Figure 28 – Possible scenarios where the NSP applies.

3.3.3 Repositioning Cost

The repositioning requirements from the system unbalance imply one Repositioning Cost that takes into account on prorated hourly cost from repositioning teams (acquisition of vans, maintenance and labor) (C_t) times the time required for these vans to move during the rebalancing period *h* (Moving time) and the time needed to take a put bicycles to their correct slots (Repositioning time) (Eq. 7). The efficiency term η comes from considering that workers and vans are not always operative and may have complementary tasks or breaks which are not moving the vans.

To find the time needed by the system to move bicycles it is calculated the distance performed by the repositioning teams within the period *h* divided by the average van speed (V_K). For the time needed to take / put bicycles, it is estimated the number of bicycles taken multiplied by two, to account for the return, for every period *h*. The δ parameter accounts to the physical time for a work put/take a bicycle on the station.

$$Z_R = \overbrace{\eta}^{Efficiency} \cdot C_t \cdot \left[\overbrace{\mathrm{Rep_{dist}}/V_K}^{Circulating\ time} + \overbrace{Rep_{mov} \cdot \frac{2 \cdot \delta}{\boldsymbol{h}}}^{Movement\ rep\ time} \right] \left[\frac{€}{h}\right]$$

Eq. 7 - Repositioning Cost.

The hypothesis that drive this section are:

- The average number of repositioning movements is equal to the average system unbalance plus the average system decentralization
- All repositioning movements must be completed every h in order to avoid an excess of accumulation
- There are two main movements performed by vans, the height unbalance generated by users not willing to go uphill; and the central-periphery unbalance where users are more likely to go to the center in a given time period (or the other way around).
- Both movements are considered independent and do not affect each other.
- Both movements can be further decomposed:
    - Long-haul trip where they will get stations completely (or almost) full and drive
    - Peddling trips where it is assumed that the truck may visit one more adjacent station to full and/or empty the van.
    - Long-hauls are predominant trips since it is preferable movements that most contribute to the general balance of the system.
    - These movements also include any other complementary unbalance within regions.
- Repositioning is done in a period h, which will set the system back to balance.
- Demand shall not be affected by it. For feasibility, the range of values must be at least from a few hours and must not exceed a whole day.

The long-haul distances are approximated by the assumption that they grow linearly with the elevation z in the height unbalance case. This means having longer trips more frequent than smaller ones, with a trip with an average $2/3\ \sqrt{R}$ distance (Figure 29). Considering the central unbalance, and assuming distances do not grow linearly when going further from the center, the distance is function of how large is the central area (φ). It is disregarded that distances could be smaller due to demand concentration within the center, so that this reflects an upper bound for the distances.

The peddling distance comes from the Transportation Problem solution where the expected distance traveled is a constant (with value 1,1) times the influence zone of one station ($1/\sqrt{\Delta}$) (C. F. Daganzo, 2005). It is assumed the vans do 2 peddling movements for every long-haul trip to account for movements that would help to fill or empty the van completely.

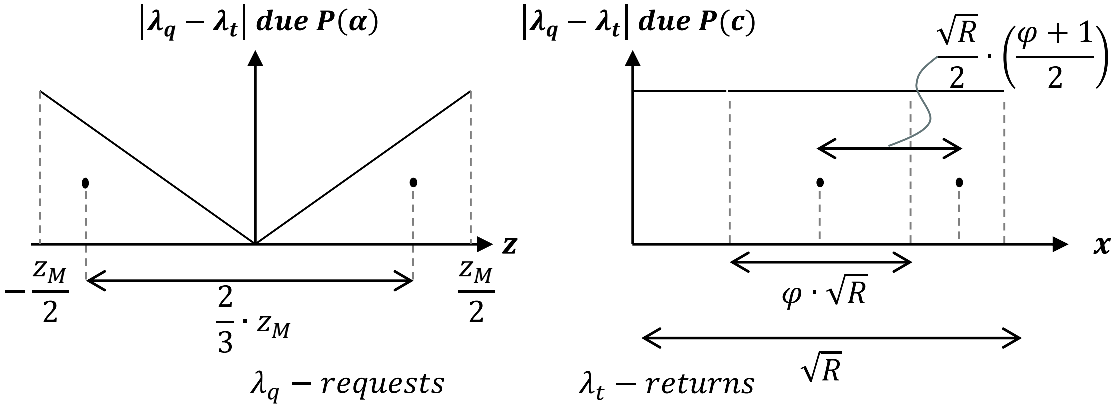


Figure 29 – Height and central unbalance trips distance.

The average unbalance in the h period considers the total number of trips that are not balanced during h. This value is calculated by integrating the net change in the number of vehicles per unit area and unit time over subzones where the elevation is bigger than the average (i.e. more requests than returns) (Eq. 8).

$$Net\ change(z) = req. - ret. = -2z\lambda P(\alpha)$$

$$Avg.net\ change\ (z) = \int_0^1 -2z\lambda P(\alpha) = \lambda P(\alpha)$$

Eq. 8 – Average unbalance within h.

The distance total repositioning distance is proportional to the average unbalance in the region and the movements described in Figure 29. To account the van size, the parameter K represents how many bicycles each van can carry on average. It is worth noticing that it does not depend directly on h although the demand sustained on h is.

$$Rep_{dist} = \overbrace{\frac{\lambda \cdot R \cdot P(\alpha)}{K} \cdot \left(\frac{2}{3} \cdot \sqrt{R} + 2 \cdot \frac{1,1}{\sqrt{\boldsymbol{\Delta_p}}}\right)}^{Height\ unbalance} + \overbrace{\frac{\lambda \cdot R \cdot P(c)}{K} \cdot \left(\frac{\sqrt{R}}{2} \cdot \left(\frac{\varphi + 1}{2}\right) + \frac{1,1}{\sqrt{\boldsymbol{\Delta_p}}} + \frac{1,1}{\sqrt{\boldsymbol{\Delta_c}}}\right)}^{Centrality\ unbalance}$$

$$= \frac{\lambda \cdot R}{K} \cdot \left(P(\alpha) \cdot \left(\frac{2}{3} \cdot \sqrt{R} + \frac{2,2}{\sqrt{\boldsymbol{\Delta_p}}}\right) + P(c) \cdot \left(\frac{\sqrt{R}}{2} \cdot \left(\frac{\varphi + 1}{2}\right) + \frac{1,1}{\sqrt{\boldsymbol{\Delta_p}}} + \frac{1,1}{\sqrt{\boldsymbol{\Delta_c}}}\right)\right) \left[\frac{km}{h}\right]$$

Eq. 9 – Distance ran by the vans to balance the system.

The reposition movements are a result of the system unbalance due to decentralization and height and central unbalances. Assuming independency between requests and returns and considering again a Poisson process, this means a $Var(\lambda_q - \lambda_t) = 2 \cdot \lambda$. This variance is computed per unit time and unit area. Then, in one repositioning interval h and in one subzone (whose influence area is $1/\Delta$) this results $2\lambda h(1 / \Delta)$. The standard deviation is defined as the root square of the variance, and this value need to be multiplied by the number of subzones ($\Delta.R$). The resulting repositioning movements are:

$$Rep_{mov} = \overbrace{R \cdot \sqrt{2 \cdot \lambda \cdot \boldsymbol{h} \cdot \boldsymbol{\Delta}}}^{Decentralization} + \overbrace{R \cdot \lambda \cdot P(\alpha) \cdot \boldsymbol{h}/_2}^{Height\ Unbalance} + \overbrace{R \cdot \lambda \cdot P(c) \cdot \boldsymbol{h}/_2}^{Central\ Unbalance}$$

$$= R \cdot \boldsymbol{h} \cdot \lambda \cdot \left(\sqrt{\frac{2 \cdot \boldsymbol{\Delta}}{\lambda \cdot \boldsymbol{h}}} + \frac{P(\alpha) + P(c)}{2} \right) \left[\frac{mov}{h}\right]$$

Eq. 10 – Number of movements done by workers to balance the system in the h period.

The number of vans needed (n) comes from the total repositioning time for the accumulated operations in a period h (Eq. 11). The necessary number must guarantee the feasibility within the period so that:

$$T = \frac{Repositioning\ time\ \cdot \boldsymbol{h}}{n} < h \rightarrow n > Repositioning\ time$$

Eq. 11 – Vans needed to perform the repositioning within h.

3.3.4 Infrastructure Cost

From the agency perspective, one significant implementation cost are bicycles and, even more, stations. On this analysis, the focus is on economic aspect rather than the financial so the acquisition is treated as a prorated hourly cost taken into account their life cycle. The Infrastructure Cost is than the number of bicycles (m) multiplied by this hourly unitary cost of bicycles (γ_{BIKE}) and number of stations (Δ.R) multiplied by its hourly unitary cost (γ_{ST}) (Eq. 12). On the station side, they are differentiated between the central ones (in $R \cdot \varphi$) and the peripherical ones (in $R \cdot (1 - \varphi)$).

Note that γ_{ST} cost bears the assumption of an equal expenditure for no matter which size of station. This can be seen as the proportional relevance of the station cost compared to the addition of some slots. This assumption shall be more feasible to low dispersions of station size from a system.

$$Z_I = m \cdot \gamma_{BIKE} + \left[\boldsymbol{\Delta_c} \cdot \varphi + \boldsymbol{\Delta_p} \cdot (1-\varphi)\right] \cdot \mathrm{R} \cdot \gamma_{ST} \left[\frac{€}{h}\right]$$

Eq. 12 – Infrastructure Cost.

While stations number is straightforward since it is a DV, bicycles are a result of these DV selection. It can be decomposed in the number of bicycles in service (m_{IS}), the unbalance (m_{UN}) from height and centrality, the system decentralization (m_{DC}), and the ones not used due because are being repositioned (m_{RP}) (Eq. 13). To arrive to the final number, a maintenance and repair factor has to be considered (ξ), since these bicycles are not available for the users.

$$m = \xi \cdot [m_{IS} + m_{UN} + m_{DC} + m_{RP}]\ [bicycles]$$

Eq. 13 - Bicycles number composition.

The bicycles In Service can be accessed through Little's Equation in queuing theory, considering the system demand multiplied by the average riding time (τ): $\lambda \cdot R \cdot \tau$.

The number of bicycles due to the unbalance (m_{UN}) can be subdivided in the height and central unbalance. The first comes from the P(α) lost trips of users unwilling to go uphill, which accounts for the lost trips accumulated during the h period of repositioning: $\lambda \cdot \boldsymbol{h} \cdot P(\alpha) \cdot {}^{R}/_{2}$. The second of the predominant unidirectional flow from periphery to the center (or the other way around) $\lambda \cdot \boldsymbol{h} \cdot P(c) \cdot {}^{R}/_{2}$.

The bicycles from the system decentralization (m_{DC}) composed by the inverse of the standard normal cumulative density function of (1-P) multiplied by the standard deviation 2.λ found previously from every station Δ.R: $R \cdot F^{-1}(1-P)\sqrt{2 \cdot \lambda \cdot \boldsymbol{h} \cdot \boldsymbol{\Delta}}$.

Finally, the number of bicycles that are not being used because they are being repositioned (m_{RP}) which is the number of vans n times its capacity K, divided by 2 since half of the trips the vans are empty going for new bicycles: ${}^{\mathrm{n} \cdot \mathrm{K}}/_{2}$.

These equations play on the safe side of the model and can be considered an upper bound to the bicycle numbers. The resulting equation is:

$$m = \xi \cdot [\ \overbrace{(\boldsymbol{\Delta_c} \cdot \varphi + \boldsymbol{\Delta_p} \cdot (1-\varphi)) \cdot \mathrm{R} \cdot \tau}^{In\ service} + \cdots$$

$$\ldots + \overbrace{R \cdot \sqrt{2 \cdot \lambda \cdot \boldsymbol{\Delta} \cdot \boldsymbol{h}} \cdot F^{-1}(1-\mathbf{P})}^{Decentralization} + \overbrace{\lambda \cdot \boldsymbol{h} \cdot P(\alpha) \cdot \frac{R}{2}}^{Height\ unbalance} + \overbrace{{}^{\mathrm{n} \cdot \mathrm{K}}/_{2}}^{On\ repositioning}\ ] \left[\frac{€}{h}\right]$$

Eq. 14 – Bicycles in a BSS.

3.3.5 Operative Cost

Finally, it is considered an Operative Cost that covers the aggregated services required to run the system such as the maintenance, administrative and so on. It is considered as proportional to the trips made which may not be true in every scenario where demand changes. For this reason, the term shall be used with caution when demand values are too apart from the ones used for calibration. One option may be attribute some factor to account for Economies of Scale that certainly exist but are hard to quantify due to the lack of available data.

$$Z_O = (\lambda \cdot R)^{f_{EoS}} \cdot \gamma_{OP}$$

Eq. 15 - Operative Cost.

3.4 Application of this methodology

3.4.1 Applicability

This methodology is conceived more as an insightful first step to grasp a system BSS ideal Decision Variables and parameters rather than a *turn-key* planning tool ready to be implemented. This comes from the simplifications assumed and the continuous modeling proposal mostly. Detailing within areas should always be done in a micro level, analyzing the regions specificities. Even so, this approach should deliver near optimal results that are a first step to the system planning.

It can also serve as a tool to draw the first parameters, guidelines and thresholds for a Public BSS bidding. This comes from the major parameters that help to orient the ideal system size and approximate costs. Nevertheless, it will always be the operators job to further detail the proposal and find ways to optimize the design in a micro level and in the overall operations.

Also, the center-periphery differentiation can serve as a phase implementation due to the nature of this systems where there is usual a first trial in the densest region, usually with the CBD in the middle of it. Once demand starts to consolidate, further expansion can be sought and the methodology could help to indicate the final design.

3.4.2 Steps

At first, the public entity or operator should define a region that there is a mobility need and political wiliness to implement a BSS. The second step would be to seek this center where most demand is and explore the area of extension of this high demand levels. The demand can be estimated through uptake scenarios associated with the population within regions or more elaborated methodologies.

The parameters referred in this work are a first step and most will show little variability, no matter where they are considered. Examples of this could be the walking speed, unwiliness to do uphill trips, repositioning times and so on. Others could have an intermediate fluctuation depend of the choices made, such as the bicycles or stations costs (depending on the technology). Others can be considered critical in the adaptability, such as region size and expected demand or value of time (mostly for less developed countries). The parameters shall be adjusted to specific situations and, although the scenarios section address the insight such changes impact the design, they could never be exhaustive enough to cover every variability.

The optimization is key, but sensitive analysis exploring neighborhood scenarios are equally important. The methodology has its bias and shall not be taken for granted as a final decision. One example is the center-periphery differentiation. Although important to exemplify a region heterogeneity, there is no reason why in reality there should be a big difference in service design when districts are connected. Smoothing this line is part of the planning phase.

Finally, the implementation should be done in phases so that each step can be felt and analyzed. Despite all efforts in a good design estimation, there will always be factors that could be of little prediction and interfere in the final system design. Be sensible to these responses from the public is also part of the system design.

3.5 Scenarios

There is a limited number of scenarios possible to be represented for not extending the work in a multitude of attempts. Three exogenous factors seemed to extend and represent a wider range of BSS: region size, population density and city wealth. The first two combined as a proxy of demand, which greatly vary between schemes. The third as a proxy to the citizen value of time (VoT) to broaden the huge differences that may exist between countries that adopt the system.

Besides the representability of those factors, it is understood that they are virtually unchangeable in short and medium terms. Significant changes in population, overall density and economic prosperity are structural factors that define a city and may take several years or even decades to show an important variance.

The region size and population density also allow an interesting trade-off comparison. Cities with the same population may present dramatically differences in their area, which implies in different densities. Which is the impact of density in a system design and overall cost is one of the questions this work touches upon.

It is worth noticing that a simplification is done regarding demand estimation. In despite of all the influencing factors listed in the literature, population was the only considered for the scenarios evaluation. Not because geography factors, climate or cycling culture are not to be taken into account, but for the sake of an easy and direct comparison. With this, it is also understood that further studies and methodologies that go deeper in the demand appraisal could solve this issue.

The scenarios proposed will be depart from Barcelona's Bicing as a calibration and then the mentioned parameters: Density-area relation and Value of Time; and, as this is a centric model, demand concentration between center and periphery and their unbalance will be tested.

4 Results

This chapter presents the main findings of this work under the methodology proposed. The parameters are the starting point and their origins can be further checked on the appendix section. The calibration brings results based on Barcelona's Bicing actual configuration, while sensitive analysis helps to validate the trade-offs and behavior of the model. The optimization explores the best design outcome for the system and possible scenarios of interest. Finally, different typology scenarios are explored to reflect the model for very different inputs to exemplify the BSS and get main insights.

4.1 Parameters

4.1.1 Barcelona's Bicing analysis

For understanding Barcelona's Bicing, this work breaks down the system in some important numbers that justify the chosen inputs. The BSS area occupies 51 central districts out of the total 73. This results in a very high population density (28.000 inhabitants/km^2) in an area of approximately 50 km^2. The 420 stations are spread in the region with significant dispersion (Chart 3), an average 8,2 station/km^2 with a 6,0 standard deviation dispersion.

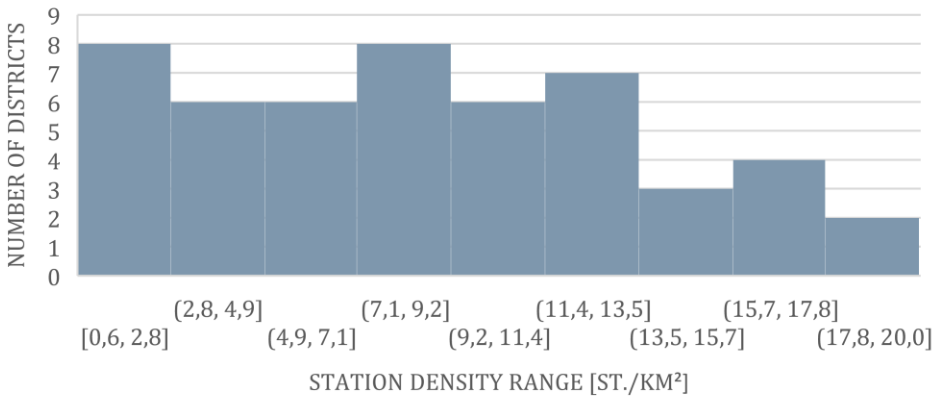


Chart 3 – Number of districts ordered by their station density.

The difference in service (slots) offered does not happen arbitrarily in the territory. Most of the highest slot concentration happens where there is more office area, or an approximate CBD (Figure 30). The red columns represent the service concentration; the blue ones, where population density is; and the blue to red spectrum, where office densities are. It can also happen some high concentration of service in the immediate proximity of this CDB where a high population is present.

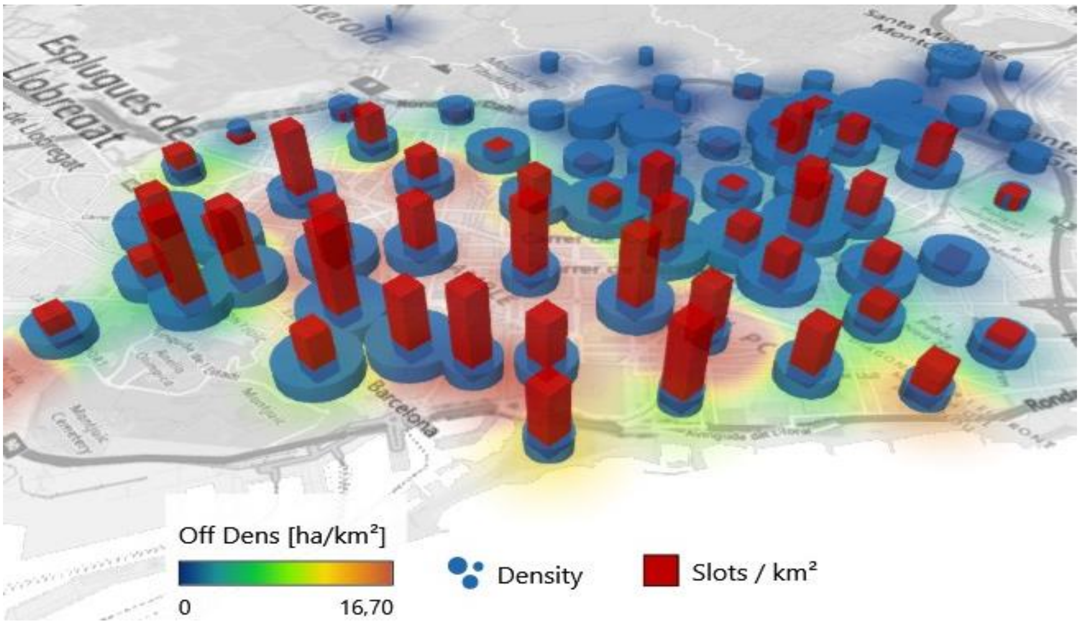


Figure 30 – Office and Population density versus slot density in Barcelona.

At first, data from Barcelona data was gathered and treated to test the system centrality. Results from the city's districts allow a visualization of service concentration towards the center and with moderate elevation (Chart 4). The chart is oriented to decreasingly show where there is more service supply concentration (slots/km²) and a pattern may be drawn. Districts with low or no BSS at all are rather far from the city center, at a much higher elevation or both. Not just it, but the there is a tendency that the further you go from the center, the less likely it is to have a high service offer.

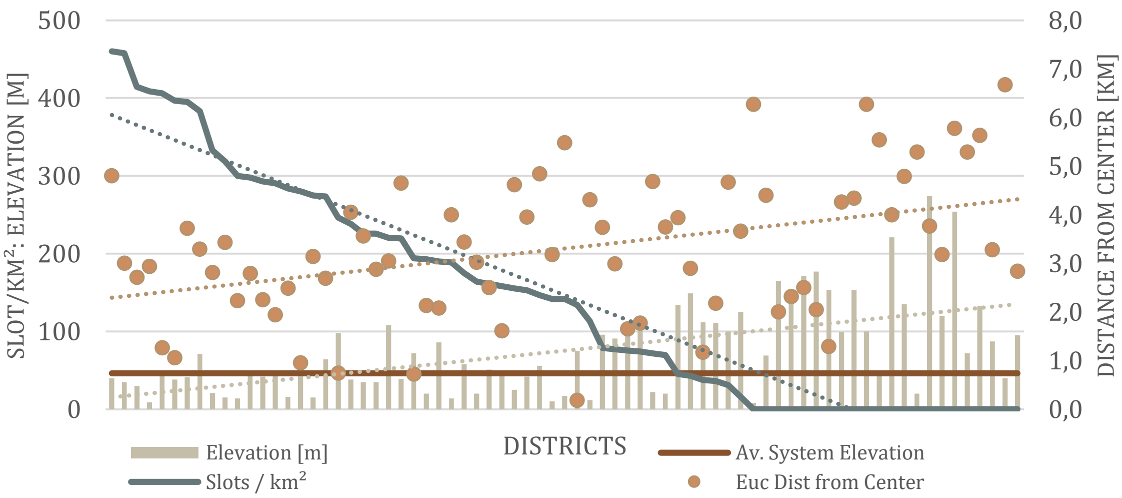


Chart 4 – System availability in the 51 districts compared to their elevation and centrality.

Demand plays a very important role, and, at the same time, it is complicated to set a single value to run the methodology since it has a significant variability across the year (Chart 5). During the year of 2017, demand went from nearly 0,9 to almost 1,5 million trips with high variability in between. This demand is stable over the past years since the system is mature and it is reasonable to assume that it shall remain like that if there are no important changes on service level. On a micro level, the pattern repeats itself. The daily variability changes considerably from a few hundreds to a nearly 5.000 request during morning peak (Chart 6). With such variabilities, how to cope with demand without incurring excessive expenditure?

It is recommended a demand level that can be hold for most of the year but not to the point where the system will be idle most of the time, for that means bad use of resources. The methodology proposed is rather conservative, so there is no point in picturing always the worst demand scenario on the worst hour, but rather, the average demand on the peak months. As such, the system will over perform during low season and shall perform accordingly during peaks. Also, as times pass by, there may is time for the system to evolve and adapt to new demand patterns. Moreover, with accurate demand pattern from an operative system, more elaborated methodologies are in hand to further determine how shall the system design evolve.

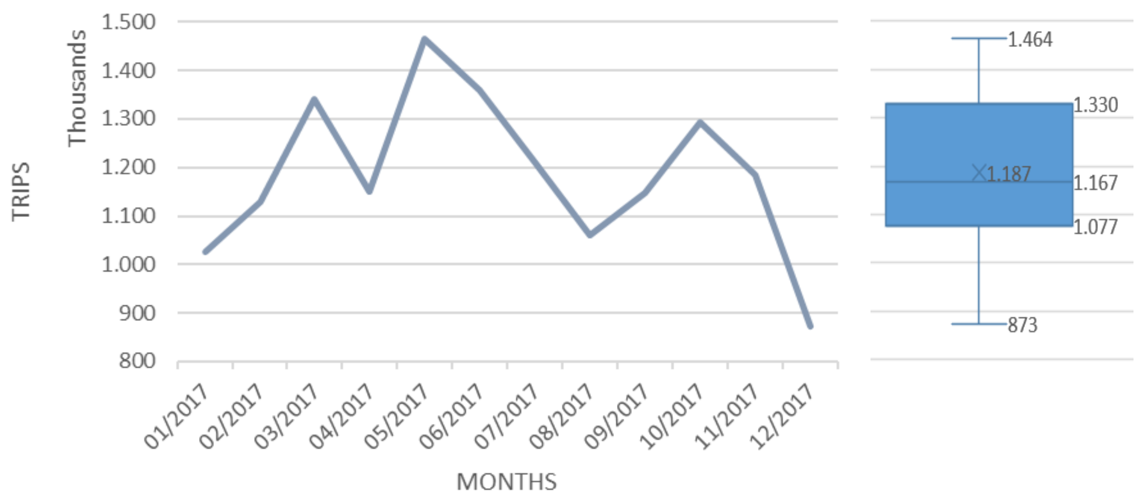


Chart 5 – Demand variability over 2017.

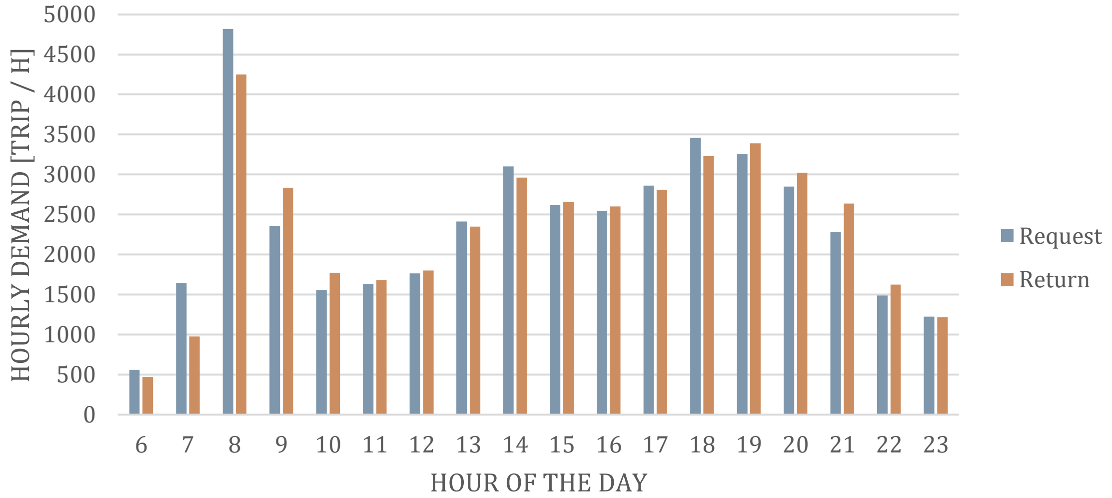


Chart 6 – Bicing hourly demand.

4.1.2 Input Parameters for the Barcelona case study

Inputs are summarized in Table 16. The first group – Area Characteristics – shall best describe a region and its particularities. It reflects the region geography (i.e. region size, central area, slopes) and demand patterns. The second, the User behavior, indicates their parameters of user characteristics (e.g. walking speed) and how will they respond to the system (depending on the VoT, for example). The last three are related to the Agency parameters on infrastructure, operation and repositioning.

The estimation process for each parameter is detailed in Appendix 1, devoted to parameter estimation. In the table there is also an assumption on the variability of each parameter, from Low (L) to High (H). A low variability will mostly vary up to ± 20%; a medium, ± 50%; while a high variability could be factors or even magnitudes higher/lower in some cases. The last ones are the most critical to be adapted.

The first group – Area Characteristics – shall best describe a region and its particularities. It reflects the region geography (i.e. region size, central area, slopes) and demand patterns. The second, the User behavior, indicates their parameters of user characteristics (e.g. walking speed) and how will they respond to the system (depending on the VoT, for example). The last three are related to the Agency parameters on infrastructure, operation and repositioning.

Table 16 – General parameters.

Groups	Parameter	Notation	Value	Unit	Variability
Area Characteristics	Service region	R	50	km^2	H
	Central demand	λ_c	60	$trip/km^2.h$	H
	Peripheric demand	λ_p	20	$trip/km^2.h$	H
	Fraction of centrality	ϕ	0,6	-	H
	Demand central unbalance	P(c)	0,02	-	H
	Average demand	λ	44	$trip/km^2.h$	H
User behavior	Walking speed	vel_w	3,6	km/h	L
	Bicycle speed	vel_b	10,2	km/h	L
	Av. riding time	τ	0,378	h	L
	Value of Time	VoT	11,40	€/h	M
	Value of Lost Time	VoLT	24,91	€/h	M
	Demand lost to slope	$P(\alpha)$	0,10	-	M
	Public Transport fare	PT_{fare}	1,02	€	M
Infrastructure parameters	Prorated bicycle cost	γ_b	0,027	€.bike/h	M
	Prorated station cost	γ_{st}	0,313	€.st/h	M
	On maintenance factor	ξ	1,15	-	M
Operation parameters	Av. trip cost	γ_{op}	0,70	€/trip	M
	Economies of Scale factor	f_{EoS}	0,95	-	L
Repositioning parameters	Van capacity	K	24	bike	L
	Van speed	V_k	21,0	km/h	L
	Transportation cost	C_t	13,6	€	M
	Inefficiency factor	η	1,5	-	L
	Bicycle repo. time	δ	0,01	h	L

4.1.3 Scenarios Typologies variations

The scenarios proposed will be depart from Barcelona's Bicing as a calibration and then the mentioned parameters will be varied according to Table 17. For a clear comparison, population, and therefore demand, are always the same (around 1,5 million inhabitants and 45 thousand daily trips). What will change is: the density-area relation from each region (depicting low density regions); the value of time of the citizens (reflecting different economic purchase power from different cities/countries); and the center-periphery factors such as demand concentration within the central region in relation to the periphery or their resulting unbalance. With this proposal, Barcelona is placed as the densest case possible, with a relatively high VoT and an average central demand concentration.

Table 17 – Parameters range for the scenarios.

Parameter	Barcelona BSS Baseline	Minimum	Maximum
Demand [trips/km²]: **(Density [ppl./km²] – Area [km])**	44 (28.000 – 50)	5,5 (3.500 – 400)	44 (28.000 – 50)
Value of time [€/h]	11,4	3,0	15,0
Central / Peripheric Demand [-]	3,0	1,0	5,0
Central / Peripheric Unbalance [%]	2	0	20

4.2 Calibration

4.2.1 Finding a center

To explore the feasibility region to place the BSS center, data of population, job and city dimensions are considered. As the systems gains strength with density rather than just absolute numbers, numbers are divided by their district areas. As result, the population is treated as density. For the jobs, it is considered the office surface of each region as a proxy of jobs that characterizes the CBD. Again, dividing by the area, one reaches the density of office surface within each district. The final point to define the feasibility boundary is the geographic center where the position of each district is averaged to arrive to the city center.

Figure 31 illustrates the region formed by these three factors where a possible center could be placed. The region is rather small compared to the city area, a 0,7 km² compared to the city's 102 km² (0,68%).

The system actual slots center is placed outside this region, 0,7 km from this region average center or 0,6 km from its closest point, the office density center. Proportionality the difference is meaningful, but when compared to the expected BSS dimensions, around 50 km² (approx. 7,1 km x 7,1 km), it falls to a less than 10% of one of these dimensions.

Having in mind the importance of the CDB to a BSS operation and knowledge of Barcelona's Eixample neighborhood relevance to the city's dynamic the office density center is considered in the following steps of this work of calibration.

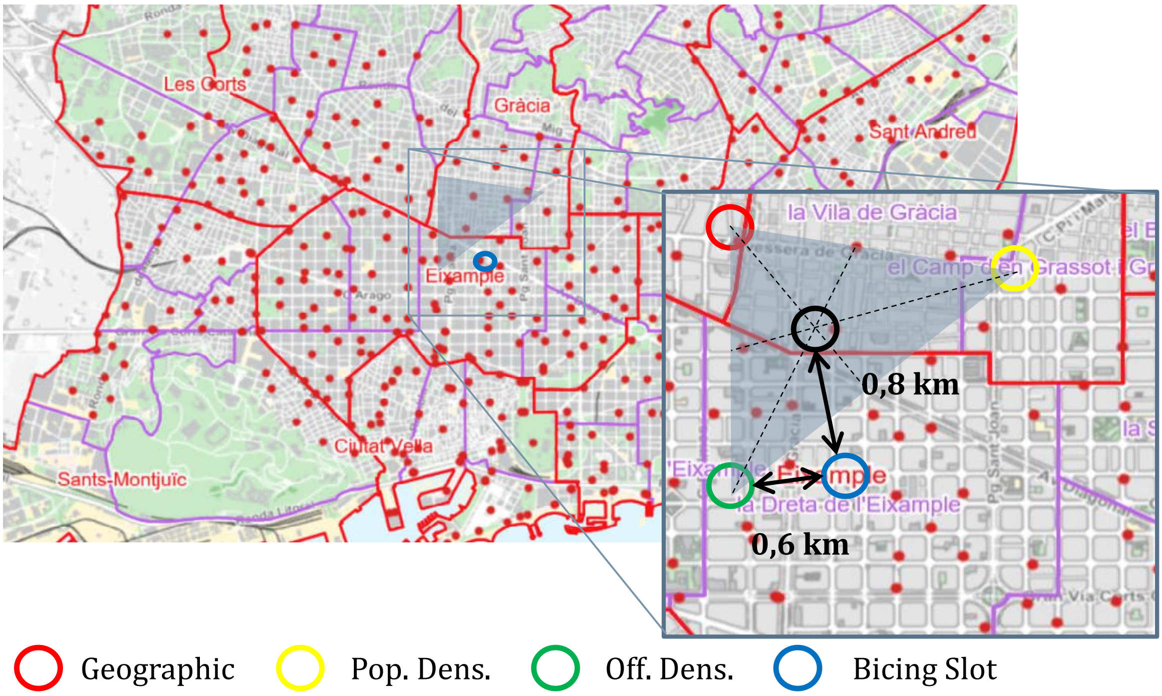


Figure 31 – Feasibility for system centers.

4.2.2 Areas extension

Each district center is ordered from the closest to the furthest from the center in order to orient which ones should be considered in the system and have a center-periphery orientation. As a filter, an elevation threshold was stablished to exclude in a first moment districts that were too high or low compared to the stablished center. The center is at a 55 m elevation from the sea level and a + 10 % is considered, so the threshold is ± 60 m, resulting in regions acceptance from – 5 m to 115 m. As a consequence, 57 from the 73 districts remained to be analyzed and included in the BSS area. In the actual Bicing, there are 51 which are part of the BSS.

On its analysis, bacc (2016) also saw the possibility of expanding Bicing a further to 10 other districts despite their complex orography (*Vall d'Hebron, La Clota, sur de Horta, La Font d'en Fargues, Can Peguera, El Turó de la Peira, La Guineueta, Verdun, La Prosperitat y sur de Trinitat Nova*), in particular with the e-bicycle aid.

To differentiate the centric region in these 57 districts, two parameters were considered with the accumulated area ordered from the closest to the proposed center: population and office areas (Chart 7). Over 85% of the population live within 50% of the territory and can be considered a possible feasible area for the system.

There is reasonable linearity in its evolution and no major change can be noticed until the 42% of the accumulated area (80% of the population), where there is a sudden slope drop. No significant centrality pattern emerged from it since this number does not allow a clear division due to the small representability of the remaining area. Therefore, the accumulated population analysis does not solve the clarify the areas limits.

On the accumulated office area, the patterns are clearer. The 60% of it is located within the 20% of the territory, while the approximate 80% is in 30%. The following 20% of the city area brings only 15% more of the office areas, which allows to see two possible cutlines for the CDB, at 20 or 30% of the territory. As the focus in on the expanded CBD, for the following steps it is considered the 30% accumulated area, which is around 60% of the total Bicing area.

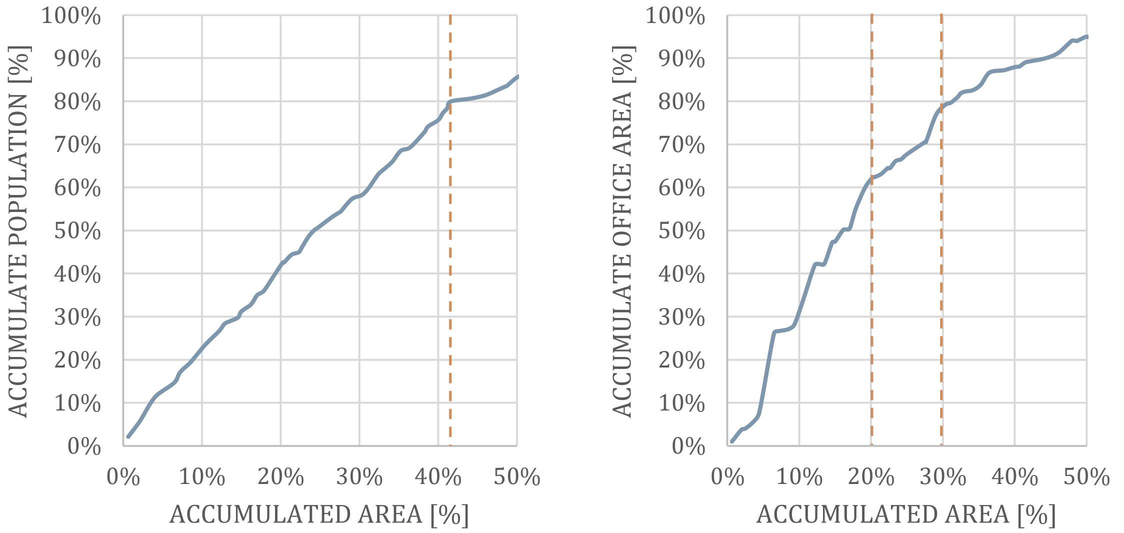


Chart 7 – Accumulated population and office area versus accumulated area, oriented from center.

As a reference, when the centrally oriented areas are contrasted with the actual request demand, the same pattern is seen (Chart 8). The 30% of the area holds 80% of the total request trips, and the 20% in the remaining area (resulting in a 3:1 λ_c/λ_p). When contrasted to the slot offer of each region, a very similar curve appears but with an average 5% below the first. Surely, a bigger supply implies in a bigger demand, but even so, this higher number holds only on this central region. There is no data to compare but is arguable that a higher supply on the periphery would raise demand at the same level as in the centric area. Even if punctually it does, it might happen that due to the center-periphery unbalance and big distances, there would be a cost not proportional to the benefits of having it. With the office and demand concentration having a notable shift in the 30% area, the calibration and analysis will be made with the 60% central region and 3:1 central/peripheric demand.

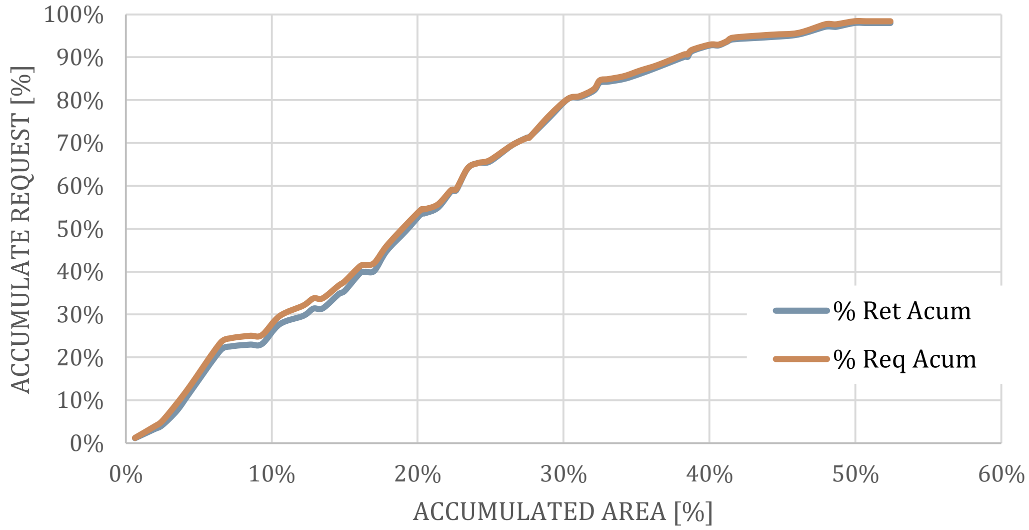


Chart 8 - Accumulated requests and slots versus accumulated area, oriented from the center.

Also, the resulting unbalance due to the centrality *P(c)* is much smaller than first thought. It is around 2% during the morning and -2% during the afternoon, resulting in an equilibrium when the whole day is considered. It is also proportionally much smaller than the height unbalance *P(α)* of 10%. It could be virtually neglected for this kind of cities, which seem to have a more homogenous use of space, and have this attention mostly when cities have a more marked land use division which results in a larger commuting trips.

4.2.3 Model outputs

The DV inputs found for the real data extracted from Bicing are in Table 18. As expected, the occurrence of empty stations is significantly higher than the full ones, almost in a 2:1 proportion on both, center and periphery.

The difference expected between zones is lightly felt in terms of NSP. The center has a 12,7% while the periphery 13,2%. This because the center presents higher full-station levels than the periphery and, although not anticipated, can be explained by its natural attraction force. The real difference comes in terms of station densities. The center has 2,4:1 stations in relation to the periphery (remembering the 3:1 demand).

Table 18 – Decision variable parameters for the calibration.

Parameter	Notation	Value	Unit
Prob. of no Serv. – Empty-Periphery	$P_{e\text{-}p}$	0,227	-
Prob. of no Serv. – Empty-Center	$P_{e\text{-}c}$	0,191	-
Prob. of no Serv. – Full-Periphery	$P_{f\text{-}p}$	0,128	-
Prob. of no Serv. – Full- Center	$P_{f\text{-}c}$	0,101	-
Station Density - Center	Δ_c	11,1	St./km^2
Station Density - Periphery	Δ_p	4,4	St./km^2
Repositioning period	h	6,8	h

Under the methodology proposed, User Costs are higher than Agency Costs (Table 19). Access Cost alone accounts for more than 40% of the Total Costs, with No Service Probability being the second higher. Both numbers help to understand the following scenarios explored, where the optimizations will focus on reducing them. Operational Costs, proportional to demand, comes in third (and the first from the Agency's perspective) and shall be taken into account. Repositioning Costs are the forth and are frequently address by the academia, searching how to optimize operations. The least impact on the overall is on the infrastructure, although it has a very strong importance on a BSS initial investment. Curiously, on the long run the bicycles present a higher cost than the stations (183 € to 130 €), an important factor to be considered when defining the BSS.

Table 19 – Costs from the model.

Parameter	Notation	Value	Unit
Access Cost	Z_A	2307	€/h
No Service Prob.	Z_{NSP}	2006	€/h
User Cost	Z_{USER}	**4313**	**€/h**
Operational Cost	Z_O	1093	€/h
Infrastructure Cost	Z_I	313	€/h
Repositioning Cost	Z_R	369	€/h
Agency Cost	Z_{AGENCY}	**1776**	**€/h**
TOTAL COST	**Z**	**6088**	**€/h**

From the data, it was possible to validate the model through calibration (Table 20). Most results are close to a 10% range in most parameters. The model seems to overestimate the required infrastructure for the input data. Reasons for that can be the conservative nature of the model and the need of more analysis of data to assure the input values are correct. This is particularly important for the P values, which present a big variability throughout the day and between days. Nevertheless, for this degree of detailing, it should be enough errors from this magnitude and that further analysis can be evaluated and explored from them.

Table 20 – Output parameters from the model compared to actual numbers.

Output Parameter	Notation	Unit	Model	Actual	Δ (%)
Bicycle	m	bicycles	6568	6000	9
Stations	St.	unit	420	420	0
Total System Slots	M	unit	11.671	10.263	13
Av. Station Size	-	Slots/st.	28	25	12
Repositioning vans	n	units	25	26	-4
Annual Op. C.	-	M€	15,6	16,0	-3
Annual Fare	-	€	149	150	-3

4.3 Optimization

4.3.1 Main result

Optimum results from model bring a very different system design (Table 21). The high Access and NSP Costs are the ones most affected since they were the highest. For the reason, DV brings all P factors to a minimum (so they are bounding – represented in yellow) and station densities much higher than the actual configuration. Station density in the center goes for its maximum (25 st./km^2 and would be 29 without the constrain) and on the periphery has an important elevation. It is interesting to notice the average 2:1 Δ_C/ Δ_P relation to the 3:1 demand proportion. This means that stations density should not necessarily follow demand concentration proportion. The repositioning remains quite similar to the original one.

Table 21 - Decision variable parameters for the optimization.

Parameter	Notation	Unit	Opt. Value	Baseline Model	Δ (%)
Prob. of no Serv. – Empty-Periphery	$P_{e\text{-}p}$	-	0,020	0,227	-91
Prob. of no Serv. – Empty-Center	$P_{e\text{-}c}$	-	0,020	0,191	-89
Prob. of no Serv. – Full-Periphery	$P_{f\text{-}p}$	-	0,010	0,128	-92
Prob. of no Serv. – Full- Center	$P_{f\text{-}c}$	-	0,010	0,101	-90
Station Density - Center	Δ_c	St./km^2	25,0	11,1	126
Station Density - Periphery	Δ_p	St./km^2	13,1	4,4	201
Repositioning period	h	h	6,1	6,8	-11

When looking to costs, User Costs are greatly reduced in comparison to the baseline (-61%) on both Access and NSP, with a highlight to the second. This impact directly the Agency's infrastructure costs, which more than doubles and Repositioning Costs, that goes up 34%. Optimum values result in 31% more costs for the agency.

Table 22 – Costs from the optimization

Parameter	Notation	Unit	Opt. Value	Baseline Model	Δ (%)
Access Cost	Z_A	€/h	1426	2307	-35
No Service Prob.	Z_{NSP}	€/h	148	2006	-91
User Cost	Z_{USER}	**€/h**	**1574**	**4313**	**-61**
Operational Cost	Z_O	€/h	1090	1093	0
Infrastructure Cost	Z_I	€/h	828	313	133
Repositioning Cost	Z_R	€/h	414	369	34
Agency Cost	Z_{AGENCY}	**€/h**	**2332**	**1776**	**31**
TOTAL COST	**Z**	**€/h**	**3906**	**6088**	**-34**

The impact of the costs increment on the system design outputs can be appreciated in Table 23. Optimum values indicate a much larger number of bicycles and station (more than double), in a way that station size remains the same. There is also an important increase in the repositioning teams, which helps to justify the improved LoS along with the bigger bicycle offer. As a result, the optimum system has a much better accessibility and bicycle availability at the expense of a bigger expenditure from the operator's side. This number (a little bit over 30% raise) sum to 20,6 M€ annual costs.

Table 23 – Optimization output parameters.

Parameter	Notation	Unit	Opt. Value	Baseline Model	Δ (%)
Bicycle	m	bicycles	15295	6568	133%
Stations	St.	unit	1012	419	142%
Total System Slots	M	unit	28084	11671	141%
Av. Station Size	-	Slots/st.	28	28	0%
Repositioning vans	n	units	35	25	40%
Annual Op. C.	-	M€	20,6	15,6	32%
Annual Fare	-	€	193,2	146	32%

There is such a remarkable change in system design that one of the main hypothesis could be affected, the demand as an exogenous factor. With a much better LoS, demand could respond and considerably increase, leading to a revaluation of the initial demand parameter and new optimum design.

4.3.2 Sensitive analysis

The model sensitivity is explored to see its limits. It is set a 5% increase in costs threshold over the Total Cost Z to verify the variability each parameter can have before reaching this limit. Each DV was changed individually while the remaining kept their optimal values. Even so, the system constrains were respected so the values still reflect feasible numbers. Results are in Table 24.

The No Service Probability Decision Variables presented a big dispersion among each other. All started bounded by the minimum constrain, but accepted different range of values until reaching the stablished 5% over cost. Empty station at the system center were the most critical and only allowed a 5,2% maximum value. This reinforces the perception of the importance of bicycle availability within this region. The one that allowed most variability, between both constrain extremes, was the probability of having full stations on the periphery.

Station density in the center was already caped, but accepted to be halved without trespassing the 5% limit. Meanwhile, peripheric station density could be varied between both extremes without reaching this threshold.

The repositioning period also accepts high variability without major cost impacts and only after the 22 hours the limit is reached. This means that the parameter has a low impact on the overall costs even with this great variability. It can also be seen as an indicator that the rebalancing problem has a complexity of its own and the model as set does not fully reflects this complexity.

Table 24 - Decision variable parameters for the optimization.

Parameter	Notation	Unit	Opt. Value	Minimum	Maximum
Prob. of no Serv. – Empty-Periphery	$P_{e\text{-}p}$	-	0,020	0,020	0,177
Prob. of no Serv. – Empty-Center	$P_{e\text{-}c}$	-	0,020	0,020	0,052
Prob. of no Serv. – Full-Periphery	$P_{f\text{-}p}$	-	0,010	0,010	0,333
Prob. of no Serv. – Full- Center	$P_{f\text{-}c}$	-	0,010	0,010	0,196
Station Density - Center	Δ_c	St./km²	25,0	12,7	25,0
Station Density - Periphery	Δ_p	St./km²	13,1	3,0	25,0
Repositioning period	h	h	6,1	3,0	22,1

4.3.3 Scenarios for Bicing

Besides the Lagrangian optimization, it is also possible to set predefined standards to verify system response to them. This approach could be useful on bidding processes where there are a set of possible requirements or trying to predict upcoming scenarios. From Bicing baseline, four variations are proposed:

- System Optimum: the optimal cost for Users and Agency (as previously seen).
- Over demand: system with 50% more demand than initially considered, allowing to predict future expansions or the natural growth of the system
- Fixed Stations: poses the possibility of altering parameters without adding / removing stations, trying to evaluate changes without incurring to stations infrastructure costs.
- Budget restrain: changes that can be done with a target Annual Operator’s Cost.
- E-bike: how e-bicycles affect the system design by decreasing height unbalance but being more expensive at the same time.

Summarized results are in Table 25 while the extended version is on the Appendix (7.1). Due to the different aspects that drive each scenario, results are quite different from each other.

Table 25 – User and Agency perspective on Bicing scenarios.

	Parameter	Notation	Unit	Opt.	1,5 λ	Fixed Δ	€ Rest.	e-bike	Baseline
User	St. Density - Center	Δc	st./km²	25	25	11	8	20	11
	St. Density - Periphery	Δp	st./km²	13	16	7	7	9	4
	Av. access walking	-	m	112	108	173	181	126	173
	Prob. No Serv.	P	-	2%	2%	4%	10%	2%	16%
	Annual Fare	-	€	184	184	155	146	210	148
Agency	Bicycles	m	unit	13518	19812	9264	8235	10074	6568
	Stations	-	unit	1001	1075	419	382	789	419
	St. Size	M/st.	slots/st.	25	34	40	40	23	28
	Rep. Teams	n	unit	30	45	32	23	34	26
	Annual Op. C.	$Z_{A\text{-annual}}$	M€	19,6	27,8	16,9	15,6	22,3	15,7

On the over demand scenario, the model increases infrastructure to cope with the new demand. As a result, there are slightly more stations (although caped by the 25 st./km² constrain), which reduces the average walking distances from users. The NSP remains at the minimum and the users annual fare is smaller than the optimum and a little higher than the baseline. On the agency's side, there would be more bicycles, stations and vans to operate the system in comparison to the optimal scenario. Annual operational costs would also rise, but not in the same proportion to the demand (result from the existing economies of scale from the model, although small).

When stations remain the same, reflecting improvements without major infrastructure investments, the optimization tries to bring NSP costs as low as possible. This is done by enlarging stations (until reaching the 40 threshold) and adding repositioning teams. The annual operational cost is 8% higher but has an improved LoS. Bear in mind that in this model stations cost the same no matter their sizes, which in this scenario impacts undervaluing the total costs.

The budget constrain scenario is insightful. With the same costs that actual operations require, optimal design suggests slightly less station density (from 8,4 to 7,6) and a focus on the NSP reduction (from 16 to 10). For this, it would be required a much higher number of bicycles (25%) and bigger stations (up to the 40 limit).

Finally, if all the system was covered with e-bicycles, station density would not reach the 25 limit due to the higher prices in installation and maintenance; it would also have a very good LoS with a 2% NSP; and have an important higher fare (42%).

The sole unanimity on the results lies in an improved Level of Service from an always lower NSP. The model systematically brings the value down to the minimum with exception to the budget constrain scenario, where it could not lower further because it would imply in higher operational costs. On this case, it was even preferable a smaller station density for compensating a better NSP.

In most scenarios, the system benefits from a higher station density, resulting in lesser walking for Users. The exception is on the budget constrain scenario where the optimum results in lesser stations, compensated by a the better NSP. A better service and bigger stations would solve the problem at the same cost from the baseline.

The systematic improvement comes with a cost. Operator's Costs and the consequently higher fare for the user are always present. The budget restrain scenario can be a solution to set an acceptable target and, at the same time, provides more specific boundaries than the general optimizations that found the model constrains as bounding.

An overview on costs complement the discussion (Chart 9). Access is always the predominant cost and optimizations try to tackle it whenever possible. NSP is a cost that rises sharply to small variations of *P* and is the first to be minimized. Infrastructure and Repositioning Costs affect each other directly. On optimal scenarios the preference is to privilege second one, at the expense of higher infrastructure costs.

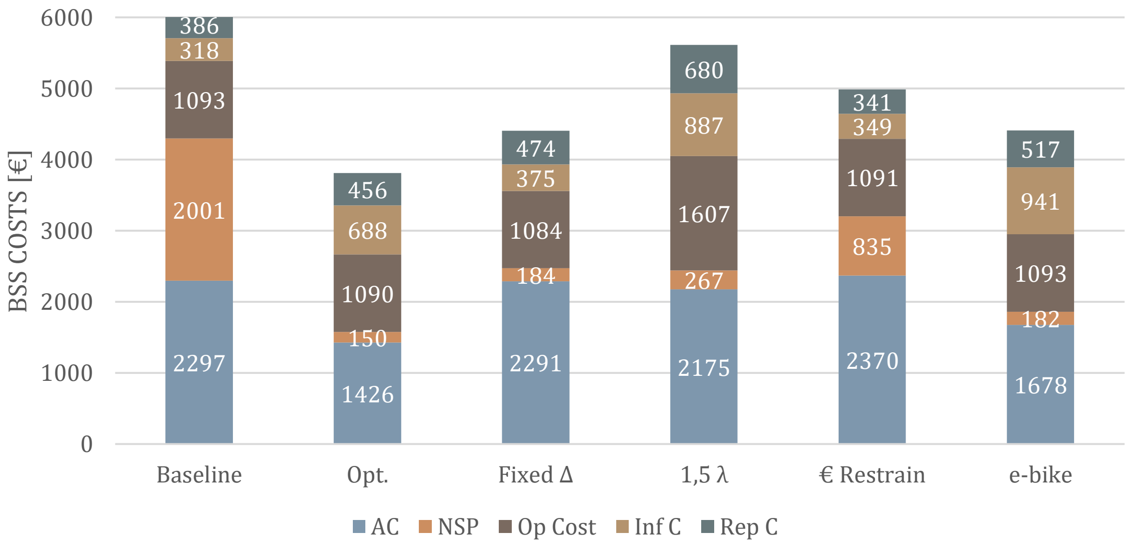


Chart 9 – Cost comparison between Bicing scenarios.

The model provides a tool to check how bidding requirements of station coverage, number of repositioning teams and standards of empty/full stations would affect them. It is also possible to check strategies of increasing bicycles, station size or number, repositioning teams and observe its effects on Users.

4.4 Different typology scenarios

A set of different scenarios are explored to further observe the changes in design. Common to all is the overall demand, which is kept for making comparisons and insights easier. Therefore, in this section, all scenarios are based on a 40.000 daily trips.

4.4.1 Demand density

There is an important assumption so the comparison is possible for different densities: demand is always proportional to population density, no matter the extent of the area. From the baseline, Bicing is the densest scenario possible with a demand of 28.000 inhabitants/km^2 in the service region of 50 km^2 with an average 44 trips/km^2. On the other extreme, it is hypothesized a 400 km^2 with an average demand of 5,5 trips/km^2, which represents a region with 3.500 inhabitants/km^2. Note that even this scenario of low density, does not cover some cities such as from the United States, with densities bellow one thousand inhabitants/km^2.

Under this premises, the model shows that BSS Design is greatly affected by demand density (Table 26). This means that cities or regions with overall low population density will present quite different outputs, even serving the same total demand. With the same total demand, a city with 1/8 of the density demand (and 8 times the area) would have 2,5 times more stations and 71% more bicycles than the high demand optimum scenario. Even so, users would have to walk 79% more and pay an annual fare 49% higher. Repositioning would be greatly impacted and would require almost twice the vehicles to keep the same LoS. As a result, costs would rise 50% between these extremes.

Table 26 – User and Agency perspective on Bicing scenarios.

	Parameter	Notation	Unit	λ=44 R=50	λ=22 R=100	λ=11 R=200	λ=5,5 R=400	Baseline
User	St. Density - Center	Δc	st./km²	25	18	12	8	11
	St. Density - Periphery	Δp	st./km²	13	9	6	4	4
	Av. access walking	-	m	112	132	162	200	173
	Prob. No Serv.	P	-	2%	2%	2%	2%	16%
	Annual Fare	-	€	184	217	244	275	148
Agency	Bicycles	m	unit	13518	17843	20294	23112	6568
	Stations	-	unit	1001	1432	1911	2508	419
	St. Size	M/st.	slots/st.	25	23	20	17	28
	Rep. Teams	n	unit	30	40	47	55	26
	Annual Op. C.	$Z_{A\text{-annual}}$	M€	19,6	23,2	26,0	29,4	15,74

For the Agency, costs proportions are shifted to the Repositioning and Infrastructure (Chart 10), going from 50% to a 70% on the overall costs from the dense to the less dense scenario. Again, the model tries to prioritize repositioning costs, which had an 83% increment, over the infrastructure, which raised 107%.

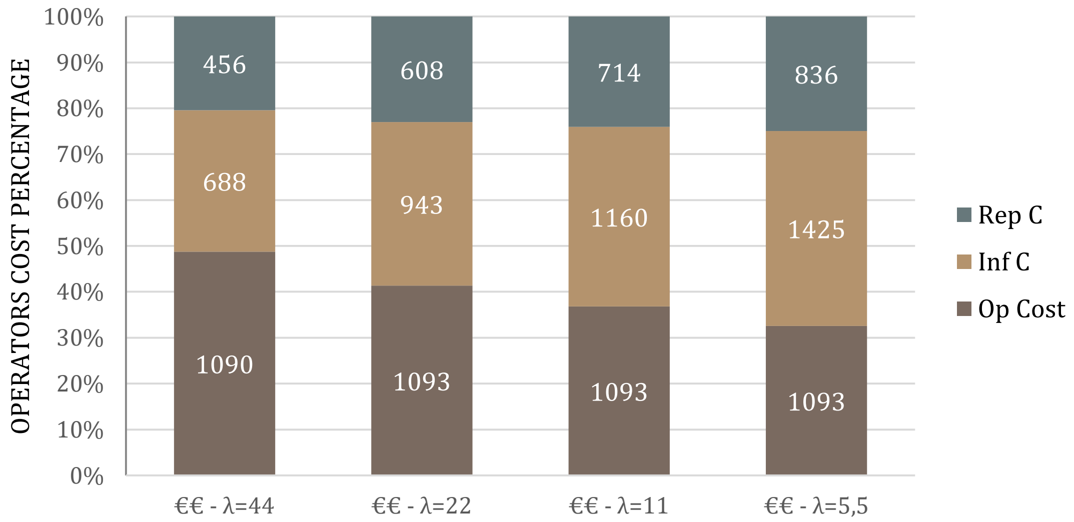


Chart 10 – Percentage cost comparison between demand densities.

4.4.2 Value of time

The Users' Value of time (VoT) is very important to the system design. This becomes evident mostly on regions where the value is low (reflecting poor societies). For them, optimum scenarios will have a more scattered station distribution and less bicycles, even so, at values not so different from Bicing's actual design (Chart 11). Densities rise sharply, mostly at the central area, and are limited when the VoT is around 10 €/h where the constrains are bounding. The Bicing system, at a VoT of 11,4 €/h, is included in this scenario and illustrates the beginning of this lower evolution, marked only by the peripheric rise of station density.

From the graph, two behaviors are worth noticing. At any point station densities go below 6 st./km^2, even at very low VoT and on peripheric regions. This can be an indicative of a minimum density that should be considered for this level of demand. The second behavior is the existence of different slopes between central and peripheric densities on the 5 to 10 VoT €/h interval. Reflecting the demand concentration, the increment on each region is always higher in the central one.

The model constrains are more present on the NSP analysis. With relatively low values of VoT (6 €/h), the system optimal already reaches the allowed threshold of 0,015. Before it, there is a very high slope, which shows the sensibility of this parameter. It seems that for much lower VoTs, the NSP could be extremely high, which also could jeopardize the system itself.

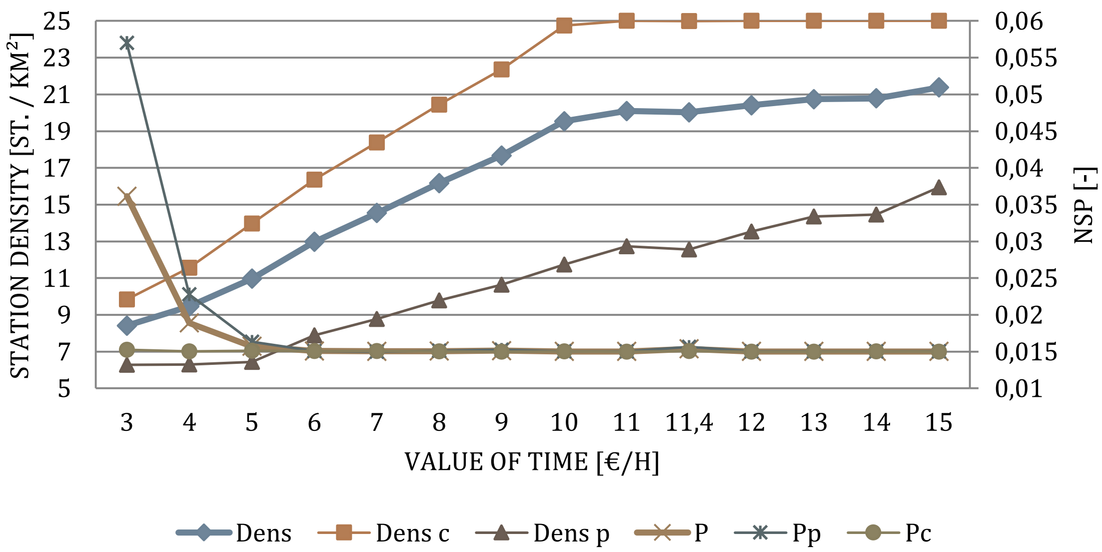


Chart 11 – Optimum station density affected by the value of time.

Joining both analyses, the demand density scenarios and the VoT decrease, allow some insights for BSS design in less developed regions. For it, it is considered a VoT of half the original, resulting in 5,7 €/h.

It is possible to see that behaviors from the outputs still hold: design is greatly affected; the system is considerably more expensive on the lowest density due to a bigger infrastructure and repositioning to cover the bigger distances (Table 27).

Nevertheless, the level of impact is different. While yearly cost on the *€€ - 44* scenario was 50% higher than the *€€ - 5,5*, on the low VoT equivalent it is 60%. Comparing two equivalent costs (*€€ - 44* and *€ - 22*), it is possible to notice an important difference in LoS in terms of accessibility: station densities go from 20 to 7,5 st./km^2.

This example shows that a low-density demand for poor regions will have the same agency operation cost as a high demand density and rich region. Even so, it is reasonable to imagine that citizens from this society will not have the means to pay for such transportation, what will result in strong subsidies required or even the infeasibility of the BSS. This decision is not to be done unilaterally nor only seeing one transportation mode, but rather the global mobility solutions available to a region and see which combination suits it best.

Table 27 – User and Agency perspective on Bicing scenarios.

	Parameter	Notation	Unit	€ λ=44 R=50	€ λ=22 R=100	€ λ=11 R=200	€ λ=5,5 R=400	€€ λ=44 R=50	€€ λ=5,5 R=400
User	St. Density - Center	Δc	st./km^2	16	10	7	5	25	8
	St. Density - Periphery	Δp	st./km^2	8	5	3	2	13	4
	Av. access walking	-	m	142	174	213	262	112	200
	Prob. No Serv.	P	-	2%	2%	2%	2%	2%	2%
	Annual Fare	-	€	169	184	203	225	184	275
Agency	Bicycles	m	unit	11970	13614	15741	17919	13518	23112
	Stations	-	unit	622	830	1102	1455	1001	2508
	St. Size	M/st.	slots/st.	35	30	26	23	25	17
	Rep. Teams	n	unit	29	34	39	46	30	55
	Annual Op. C.	$Z_{A\text{-annual}}$	M€	18,1	19,7	21,6	24,0	19,6	29,4

Looking into the scenarios costs for the agency, it becomes clear a much higher infrastructure costs evolution in the high VoT scenario €€ in comparison with the low one € (Chart 12). In a slightly lower scale, the same happens with the repositioning costs. On both cases, this highlights the huge impact density can have on transportation costs, including BSS, and how design should reflect it along with economic feasibility to the local context.

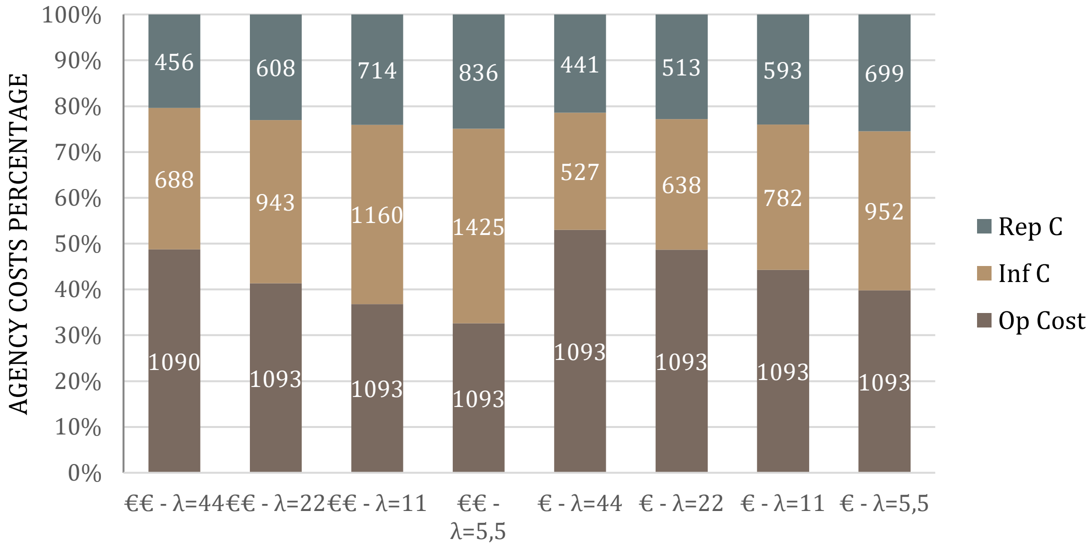


Chart 12 – Operators costs according to density and VoT scenarios.

4.4.3 Central demand concentration

Demand concentration is changed from the initial 3:1 baseline. It goes from a 1:1, which represents a homogeneous demand to a 5:1 scenario, where demand is highly concentrated (Chart 13). On the 1:1 scenario, there is a slight differentiation from center to periphery due the unbalance between regions. Already from a 2:1 relation, the central region reaches the 25 threshold. As the proportion progresses, the station density correspondence is not linear. The 5:1 demand has a 2,5:1 station proportion. Even when the constrains are relaxed, peripheric station density remains virtually the same and the central one has a not so strong increment (Chart 14).

Costs are slightly affected, demonstrating Economies of Scale, but at a limited rate (Chart 15). Repositioning and mostly, Infrastructure Costs are smaller on high concentration scenarios. This is partially explained by the constrain of station densities. Nevertheless, when this constrain is taken, this behavior is still present, even though in a smaller degree. On this model, demand concentration is relevant for this EoS on the agency mostly and in a smaller proportion, to the User Access. This value gets bigger due to the constrain, but when it is relieved, access costs are smaller the more concentrated is demand.

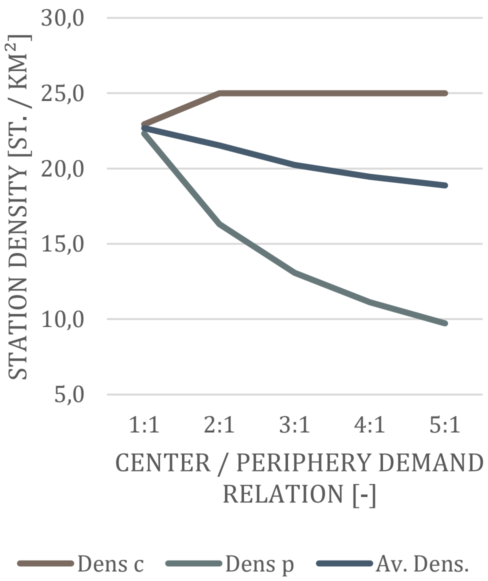


Chart 13 – Station density variation due to demand concentration.

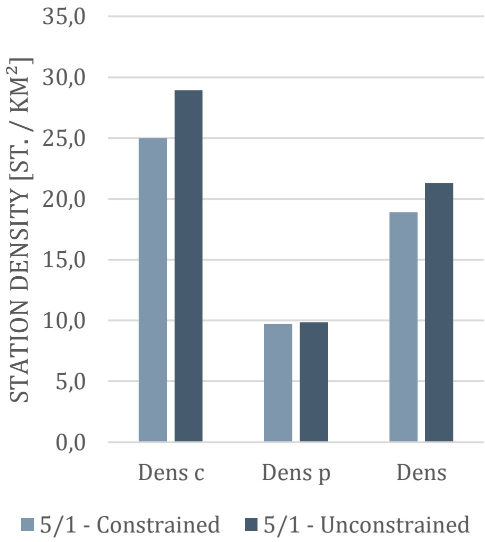


Chart 14 – Station density disregarding model's constrains.

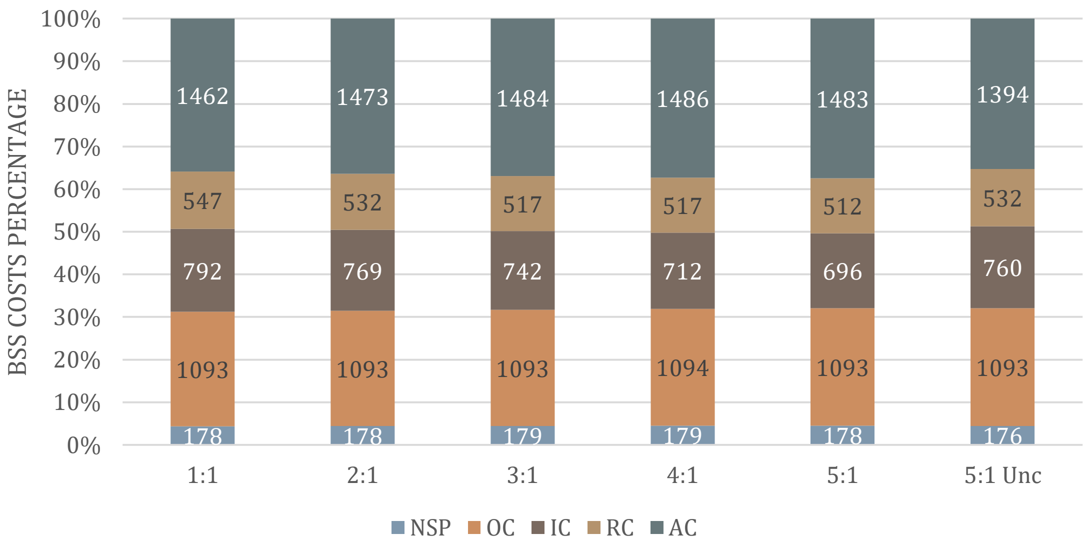


Chart 15 – Cost comparison on different demand concentration scenarios.

4.4.4 Central unbalance variation

When the central unbalance P(c) is varied, the biggest impact is on the increase of the necessary vehicles for repositioning. They go from 33, on the no unbalance scenario, to 46, when the unbalance is at 20%, resulting in a 39% raise in the number of vehicles. This impacts directly the agency, that would have a 5% extra costs on overall operation. Curiously enough, this would imply in lesser stations and bicycles since the LoS can be kept by this extra fleet of vans. This decrease in the station densities is only felt in the periphery since the central area is on the maximum threshold of 25 stations/km².

As a reference, the optimum scenario is closer to the 0% unbalance since the number is at 2%. It is possible that if decision makers expand the area of service further, this number could be higher since a more residential periphery can be possible and the central region becomes better defined.

Table 28 – User and Agency perspective on Bicing scenarios.

	Parameter	Notation	Unit	0%	5%	10%	15%	20%	Baseline
User	St. Density - Center	Δc	st./km²	25	25	25	25	25	11
	St. Density - Periphery	Δp	st./km²	14	12	11	9	8	4
	Av. access walking	-	m	110	112	114	115	117	173
	Prob. No Serv.	P	-	2%	2%	2%	2%	2%	16%
	Annual Fare	-	€	191	195	199	202	204	148
Agency	Bicycles	m	unit	14951	15655	14974	14918	14527	6568
	Stations	-	unit	1024	989	966	938	919	419
	St. Size	M/st.	slots/st.	27	28	28	28	28	28
	Rep. Teams	n	unit	33	35	40	43	46	26
	Annual Op. C.	$Z_{A\text{-}annual}$	M€	20,4	20,8	21,2	21,5	21,7	15,74

5 Conclusion

The number of public bicycle systems in the world has experienced a truly exceptional rate of growth. It seems that there is a convergence from car-centric scenarios to more active mobility schemes. The reported number of established systems continues to increase, leaving no doubt about its position in the world as a public transportation mode. Finding useful methods to support decision-making in near optimal choices becomes important in this ever growing scenario.

5.1 Main contributions

This thesis develops an analytical planning model for a “one-way station based bicycle sharing system” with center-periphery differentiation. This is based on the modeling of the strategic variables of the system and their relevant trade-offs, using continuous approximations. This analytical approach requires a simplification of the reality (e.g. assumption of spatially uniform demand level within each area) and to obviate some details of operation.

This work contributes on its attempt to draw some quick design outlines for a series of possible scenarios that represent the realistic examples of cities, from dense to sparse; from rich, to less developed. An important point for the model proposed was the differentiation in the center-periphery relation. Different demands require a different design and the system gains strength from the correct choice of elements. More, the model can be useful to plan implementation phases, first designing and consolidating the central region and then, further expanding it to a periphery with less demand.

The model calibration on Barcelona’s *Bicing* showed reasonable numbers, around the 10%, which is acceptable for this level of simplification assumed in the model. Optimization reveals a big gap between current and optimum design, showing a much denser station placing needed. Although numbers seem high, densification has the purpose to distribute demand better among nearby stations and having smaller walking distances, which contributes to a more reliable service. On the same way, the number of bicycles rose accordingly. Besides, the LoS due to the No Service Probability (NSP) went to the minimum determined by the model constrain. This last behavior was repeated systematically. The model always tries to bring it to a minimum.

When analyzing the *Bicing*’s scenarios from this optimal one, it is possible to notice strategies to improve the system when there are certain standards to attain. With the same budget that runs the system, design should privilege a better NSP, even at the expense of a lesser station density. When the stations numbers are untouched, having bigger stations and reinforcing the number of repositioning vans could contribute greatly to the NSP (from 16% to 4%) costing only 8% more than the baseline. If demand was 50% higher, costs would go up, but not at the same proportion. This can be useful to plan future scenarios of demand consolidation when the system is new. Finally, the fully electric bicycles system would rise costs, not compensating the benefits of having smaller height unbalances, at least for the prorated e-bikes costs used. Since technology helps to bring values down, it is quite possible that soon the system will be feasible, if not preferable than the non-electric option.

The new scenarios proposed helped to see how the model is affected by inputs of high variability and that can exemplify and give guidelines to regions different from the Barcelona case. This because Barcelona is one of the densest cities in Europe and within the Bicing service region, population density goes almost to 30.000 inhabitants/km^2.

Demand density showed a huge impact in the BSS design. Serving the same demand in larger and less dense regions can make costs rise sharply: more stations, bicycles and vans are required to cope with the larger area. At the same time, LoS goes down since these extra infrastructures do not rise proportionally to the region area, making users walk more.

This becomes critical when seen together with different levels of Value of Time (VoT). Basically, if citizens and society do not have the economic means, low density regions could make the system unfeasible. Also, the loss in the LoS when density goes down in much more important for the low VoT cases.

Regarding the centrality, it was possible to see that demand concentration also affects design and shows some degrees of Economies of Scale. Basically, the higher central demand is over the peripheric, the lesser will be the average walk for the user and the fewer infrastructure is required. This means that a higher number of users benefit from the high central density while a smaller number of them are penalized by the smaller station densities in the periphery, which goes down considerably.

When analyzing the unbalance between zones, as expected, the bigger unbalance generates extra repositioning costs, with much more vans needed. Even so, looking at the overall costs, there is only a 5% increase comparing the no unbalance to the 20% P(c) unbalance. Also surprisingly, Barcelona scores very low on this, only 2% considering the morning period (and -2% in the afternoon). More data from *Bicing* and other cities should be gathered to draw a conclusion.

In resume, a monocentric approach allows a clear definition of boundaries within a region where service levels can be adjusted according to demand and an overall cost. Later smoothing this zone differentiation can bring reality to the model. It is also possible to set different scenarios of an operating system regarding seasonality, demand fluctuations and regional differences, which makes the model useful. Results proved to be robust, where clear patterns emerged even when input variability was high. It also attempts to build the base to comprehend the localization of BSS. Understanding how BSS can be locally implemented can have long-term positive effects through creating a cycling culture and changing peoples' travel behaviors and their habits.

5.2 Limitations

This work was based under certain assumptions and excluding some topics of interest that could affect results. Mainly, a more accurate demand estimation would bring more clarity along with some understanding of its exogenous assumption since it is expected demand changes when design changes dramatically in some scenarios. Also, the model itself has some *bias* and trying different sets of configurations could help confirming if this one proposed is the most adequate.

An example is the preference always for a minimum NSP, which would be unfeasible if it were not by the constrains established. In addition, the proposed differentiation between empty and full stations and central and peripheric ones do not bring better insights if their values are always fixed at a minimum. On the other hand, the exception for this was on the budget constrain scenario, where a clear differentiation between the four *P* variations was found. Besides, it is backed up by a real case where *Bicing*'s bidding proposes these differences.

Also the high density of stations proposed for the level of demand is substantially high and has only a few neighborhoods that actually are close from such numbers. It can also be argued that always a bigger system does not necessarily imply in better system performance as some practitioners imply, promoting the network effect (Médard de Chardon et al., 2017).

5.3 Further research

The analytical model presented here represents a simplification of reality, which is essential to obtain global insights regarding the optimization of the system from the planning perspective. Further research could go in two directions.

A first is further exploring the model and comparing it to different scenarios across the globe. It can be useful to confront it with other real examples besides the one from Barcelona. This would allow to calibrate it further and make it even more robust, without incurring to more complexity.

A second direction could be attempting new approaches to mitigate the differences between the model and reality, in order to test it and obtain the order of magnitude of the errors committed. This could include the relaxation of the assumption of spatially constant demand, including variable demands in central regions and periphery, and a discrete modelling approach to account for the particular behavior of individual customers, vehicles, trips and repositioning operations. In this case, continuum approach could become too complex to be modeled and the development of a simulation would be easier to accomplish these objectives.

Going a little further, beside these two directions, future research could also address the potential of new technologies (free floating BSS) and management strategies (smart pricing, user incentives, bookings, etc.) to reduce the need for relocation movements in order to promote user-based relocations.

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7 Appendix

7.1 Estimations & Sources

7.1.1 General parameters

Groups	Parameter	Notation	Value	Unit	Source
Area Characteristics	Service region	R	50	km^2	Llopis (2016)
	Central demand	λc	60	$ppl/km^2.h$	Check 7.1.2
	Peripheric demand	λp	20	$ppl/km^2.h$	Check 7.1.2
	Fraction of centrality	φ	0,6	-	Check 7.1.4
	Demand central unbalance	P(c)	0,02	-	Check 7.1.4
User behavior	Walking speed	velw	3,6	km/h	https://en.wikipedia.org/wiki/Preferred_walking_speed
	Bicycle speed	velb	10,2	km/h	Llopis (2016)
	Av. riding time	τ	0,378	h	Llopis (2016)(Llopis, 2016)
	Value of Time	VoT	11,40	€/h	Llopis (2016)
	Value of Lost Time	VoLT	24,91	€/h	Llopis (2016)
	Demand lost to slope	P(α)	0,10	-	Llopis (2016)
	Public Transport fare	PTfare	1,02	€	https://www.tmb.cat/en/barcelona/fares-metro-bus
Infrastructure parameters	Prorated bicycle cost	γb	0,028	€.bike/h	Adapted from Llopis (2016)
	Prorated station cost	γst	0,311	€.st/h	Adapted from Llopis (2016)
	On maintenance factor	ξ	1,15	-	http://bikes.oobrien.com/barcelona/
Operation parameters	Av. trip cost	γop	0,70	€/trip	Adapted from Llopis (2016)
	Economies of Scale factor	fEoS	0,95	-	Arbitrary
Repositioning parameters	Van capacity	K	24	bike	Interview at B:SM[2]
	Van speed	Vk	21,0	km/h	Llopis (2016)
	Transportation cost	Ct	15,2	€	Adapted from Llopis (2016)
	Inefficiency factor	η	1,5	-	Adapted from Llopis (2016)
	Bicycle repo. time	δ	0,01	h	Llopis (2016)

[2] Interview with, head of the Reseach area at B:SM (Barcelona Servicis Municipals).

7.1.2 Demand

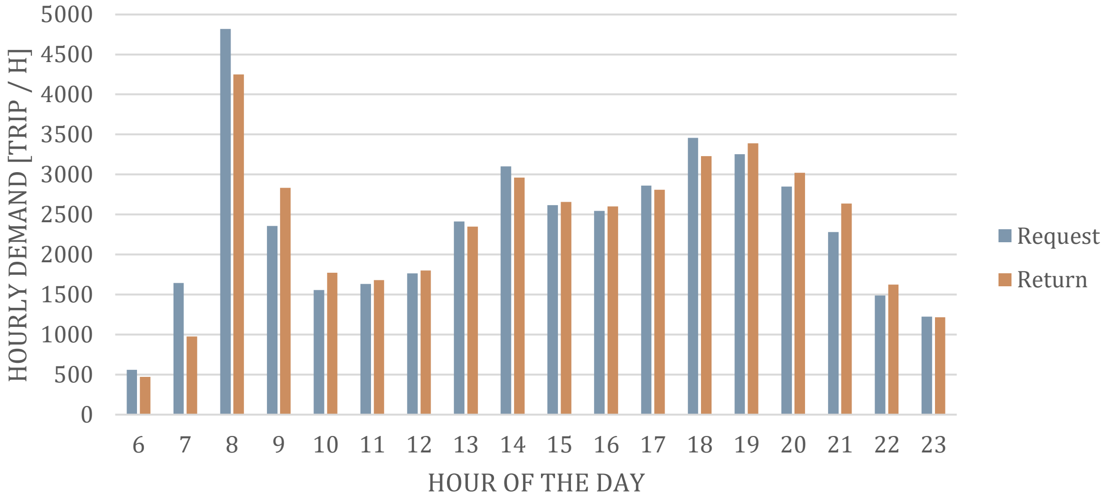
The data recorded and used in this thesis was obtained from a web service provided by Clear Channel[3]. This website is updated every minute with information of the system: number of bicycles and free spots in each station, and precise information on the location and the status of the stations.

Information is recorded every minute, including the dynamic data (number of bicycles and free spots at each station) and the static one (topographic characteristics of each station – longitude, latitude and height). Static data is invariable in time, so it is recorded once and stored for future calculations.

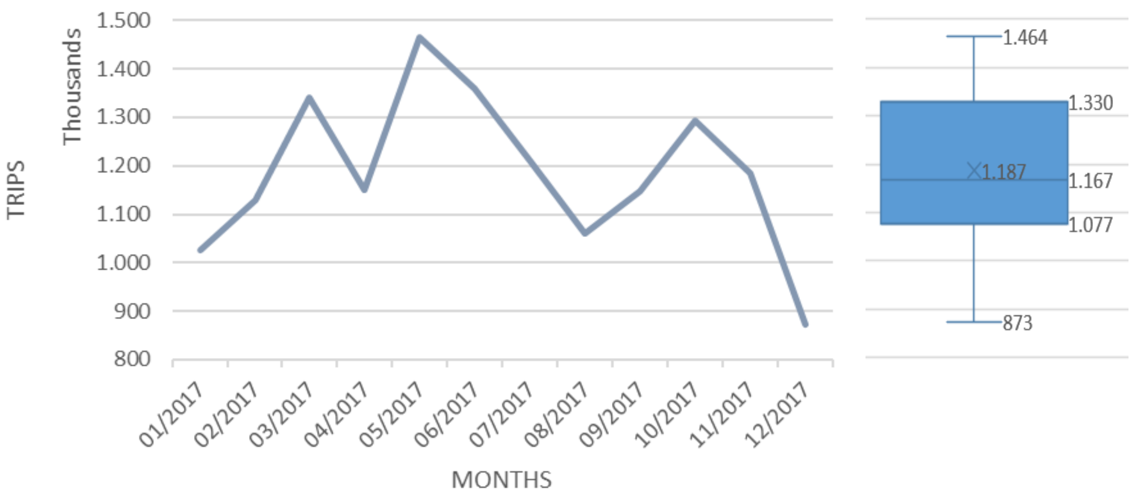
The difference in the number of bicycles in a station between two consecutive minutes will give the number of requests (negative difference) or returns (positive difference) in that station. It is important to notice that this number of requests and returns include those variations due to repositioning, so to obtain real demand these rebalancing operations need to be removed. Nonetheless, despite this correction, this demand is not still real demand. This difference is in fact the difference between the requests and returns in that station in that minute. It could be possible that the difference between two consecutive minutes is zero and still have demand (same number of requests and returns). In order to neglect this phenomenon, an assumption is made: there is only one type of operation in a particular minute. It is accepted, by making this assumption, that there is a slight underestimation of the total demand.

It has been considered that if the difference in the number of bicycles is minus four for lower (requests), or three or higher in one minute (returns), this is due to repositioning and not demand. This threshold has been determined from observation of the system and is justified in the next section. Once repositioning is taken into account, the total requests and returns that happened every minute in every station during the measurement hours are obtained. By simply adding the requests in all the stations, the total requests per minute in the system are obtained. If the requests per minute are added during the whole measurement time, and divided by the total measurement hours (18), the average hourly requests (or returns) can be obtained. If this result is divided over the area R of the service region, then the hourly average demand per square kilometer is finally obtained. Data recording took place during a working day, the Feb, 23th, 2017. The same procedure could be applied to any other day to obtain similar results.

[3] http://wservice.viabicing.cat/v1/getstations.php?v=1



That was typically a high demand day from an average demand month as seen below. Yearly data was retrieved directly from the Bicing website[4].



To differentiate demand between their regions, central and peripheric, data from each station was retrieved, and then associated with their respective district and neighborhood. When the central area was defined (as seen in 4.2.2), it was just a matter of seeing the requests of each one of the neighborhoods that composed the central area.

Considering the 30% central region, accumulated requests sum to 33.096 trips. The remaining area had the 42.435 trips, resulting in 9339 trips. Dividing them by their respective area, 31,0 and 22,6 km^2, the demand density per trips are 1.068 trips/km^2

[4] https://www.bicing.cat/ca/content/informaci%C3%B3-del-sistema

and 413 trips/km^2. Considering that the data is gathered from 6:00 to 24:00, there is 18h of collection and finally the demand from each region is 60 and 23 trips/h.km^2. As a simplification, it is considered a full 3:1 demand relation, used in the model.

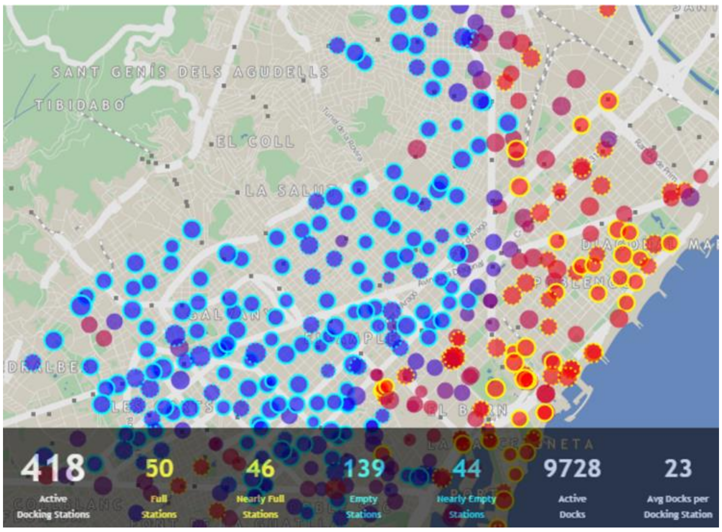
7.1.3 No Service Probability

The No Service Probability comes from the counting how many minutes stations were full or empty along the day. The area differentiation follows the same strategy as the demand, presented above.

For calculating each value, it was summed these minutes, from each station and again they were gathered according to neighborhoods and districts. The numbers were then summed and divided by the number of stations in each region (347 and 105), and again by the 1080 minutes from the 18 hours of data gathered.

Parameter	Notation	Value	Unit
Prob. of no Serv. – Empty-Periphery	$P_{e\text{-}p}$	0,227	-
Prob. of no Serv. – Empty-Center	$P_{e\text{-}c}$	0,191	-
Prob. of no Serv. – Full-Periphery	$P_{f\text{-}p}$	0,128	-
Prob. of no Serv. – Full- Center	$P_{f\text{-}c}$	0,101	-

Although not explored in this work, by following the P along the year of 2017, it was possible to see a great variability in these numbers. On the most critical day on July, 15th, 2017, the values ended up being up to 43%. So, unlike other results that shall present low variability, an accurate NSP should be fruit of months of data analysis, confronted with demand so clear behaviors can be seen.



Source: http://bikes.oobrien.com/barcelona/

7.1.4 Centrality

The whole model was based on the center periphery differentiation. So it would be an important part to quantify the unbalance generated by it. For doing so, requests and returns were calculated along the day on each region. If requests and returns in each region did not match, this would be the resulting P(c).

When the whole day was considered, the differences on both regions were virtually null (5 / 33.096). If taken only the morning period, results were more clear, a 2,4% (441 / 17.044) towards the center. It can be understood that in the afternoon there is an inverse flow that makes the system with the overall 0% unbalance.

Since this unbalance impacts mostly the repositioning, the 2,4% was considered because the rebalancing periods were always around 6 hours and never were close to the whole day. Considering the whole day would underestimate the repositioning needed.

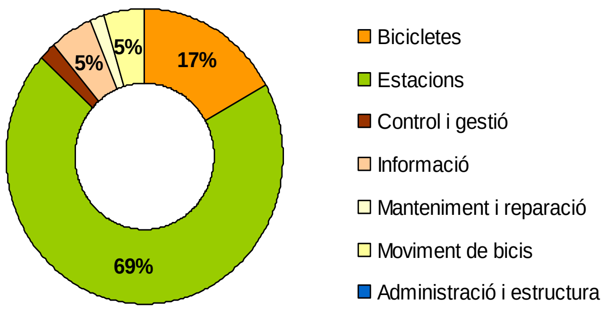
Also, the fraction of center to center or periphery to periphery factors (f_c and f_p) should lead to the P(c) unbalance. But in practice, it was not possible to determine these numbers, but rather, have a set of combinations that could correspond to their values. This can be understood on the equation below, that leaded to the P(c). Both variables are unknown while all the others were identified. The result of this in a line of solutions in a graph.

$$P(c) \cdot \lambda = \overbrace{(1 - f_p) \cdot \lambda_p \cdot (1 - \varphi)}^{p \to c} - \overbrace{(1 - f_c) \cdot \lambda_c \cdot \varphi}^{c \to p}$$

7.1.5 Costs adapted

Although most parameters was retrieved from Llopis (2016), there were some overestimated costs which lead to an over 50% cost estimation. This section makes some corrections that allowed the correct calibration of these parameters.

For this revaluation, it was consulted Lopez (2009), who worked at B:SM, in close contact with Bicing's operations. Total operations correspond to 10,2 M€/year and comprises 26 vans and 230 staff.



INVESTMENT COSTS
6000 bikes, 400 stations
15,9 M€

OPERATIONS COST
230 staff, 26 trucks
10,2 M€/year

Source: Adapted from Lopez (2009).

<u>Transportation Costs – C_t</u>

Accounting the 10,2 M€/year, for the 26 repositioning teams and dividing by the hours in one year:

$$C_t = \frac{10.200.000 \cdot 0,304}{24 \cdot 365} = 13,6 \ \frac{€}{h}$$

<u>Inneficiency factor - η</u>

Instead of assuming a 100% productivity, in this work it is considered a 50% inefficiency factor. Otherwise, it would be assuming that workers immediately start working taking and putting bicycles when not driving, with no breaks, no other administrative tasks or any other losses.

Operative Costs - γ_{op}

The previous value was 0,63 €/trip which totalized operative costs around 1100 €/h for that level of demand (Llopis, 2016). Although the new value is 0,70 €/h, it is to reflect the same hourly cost. The new value comes from the new Economies of Scale factor that could reflect some savings when demand is changed.

Although demand in Llopis (2016) is 36 trips/km^2.h, it was divided by a 24 hours period. This underestimates the average demand, since no data is available from 0:00 to 6:00, but already at 6:00, demand is virtually none compared to the rest of the day. For that reason, this work considers correct to divide the total demand by 18 hours, which results in 44 trips/km^2.h, coinciding with the demand level used here.

Prorated bicycle cost - γ_b

Calculating the values for the bicycles, considering the 22,4% of operational and maintenance costs that correspond for bicycles and dividing by the 6000 bicycles in the system:

$$\gamma_b = \frac{10.200.000 \cdot 0{,}224}{24 \cdot 365 \cdot 6.000} = 0{,}04\ \frac{€}{h \cdot bicycle}$$

Since these costs comprise in maintenance, they are partially covered by the Operative Costs considered. Another approach is tried then. According to Clear Channel, each bicycle costs 400€. Considering a short lifespan of 1,7 years, bicycle costs are:

$$\gamma_b = \frac{400}{24 \cdot 365 \cdot 1{,}7} = 0{,}027\ \frac{€}{h \cdot bicycle}$$

Prorated station cost – γ_{st}

Considering the 19,5% of operational maintenance for stations and dividing by the 420 existing in the system:

$$\gamma_{st} = \frac{10.200.000 \cdot 0{,}195}{24 \cdot 365 \cdot 420} = 0{,}54\ \frac{€}{h \cdot station}$$

Again, this value includes maintenance and it is not the focus of this parameter. Look to the investment creates another opportunity. Taking the 69% from the 15,9 M€ initial investment, results in the money spend on stations. Assuming a lifespan of 10 years, and the 400 stations, their prorated cost would be:

$$\gamma_b = \frac{15.900.000 * 0{,}69}{24 \cdot 365 \cdot 10 \cdot 400} = 0{,}313\ \frac{€}{h \cdot station}$$

7.2 Comprehensive results

7.2.1 Barcelona Bicing

	Parameter	Notation	Unit	Opt.	Fixed Δ	1,5 λ	€ Restrain	Baseline
Decision Variables	Prob. of no Serv. – Empty-Periphery	$P_{e\text{-}p}$	-	0,020	0,020	0,177	0,109	0,227
	Prob. of no Serv. – Empty-Center	$P_{e\text{-}c}$	-	0,020	0,020	0,052	0,040	0,191
	Prob. of no Serv. – Full-Periphery	$P_{f\text{-}p}$	-	0,010	0,010	0,333	0,036	0,128
	Prob. of no Serv. – Full- Center	$P_{f\text{-}c}$	-	0,010	0,010	0,196	0,019	0,101
	Station Density - Center	Δ_c	St./km²	25,0	12,7	25,0	0,051	0,162
	Station Density - Periphery	Δ_p	St./km²	13,1	3,0	25,0	7,4	11,1
	Repositioning period	h	h	6,1	3,0	22,1	4,8	4,4
System Cost	Access Cost	Z_A	€/h	€ 1.484	€ 2.307	€ 2.150	€ 2.665	8,4
	No Service Prob.	Z_{NSP}	€/h	€ 180	€ 218	€ 266	€ 539	6,8
	User Cost	Z_{USER}	€/h	€ 1.663	€ 2.525	€ 2.416	€ 3.204	€ 2.297
	Operational Cost	Z_O	€/h	€ 1.093	€ 1.093	€ 1.607	€ 1.093	€ 2.001
	Infrastructure Cost	Z_I	€/h	€ 741	€ 389	€ 900	€ 293	€ 4.297
	Repositioning Cost	Z_R	€/h	€ 518	€ 419	€ 694	€ 393	€ 1.093
	Agency Cost	Z_{AGENCY}	€/h	€ 2.352	€ 1.901	€ 3.201	€ 1.779	€ 318
	TOTAL COST	Z	€/h	€ 4.015	€ 4.426	€ 5.617	€ 4.983	€ 386
Design outputs	Bicycle	m	bicycles	15295	9280	19835	6950	€ 1.797
	Stations	St.	unit	1012	419	1115	318	€ 6.094

	Total System Slots	M	unit	28084	16589	36365	12219	6568
	Av. Station Size	-	Slots/st.	28	40	33	38	419
	Repositioning vans	n	units	35	28	46	26	11671
	Annual Op. C.	-	M€	20,6	16,7	28	15,6	28
	Annual Fare	-	€	193	156	175	146	25

7.2.2 Demand scenarios

	Parameter	Notation	Unit	€€ - λ=44	€€ - λ=22	€€ - λ=11	€€ - λ=5,5	Baseline
Decision Variables	Prob. of no Serv. – Empty-Periphery	$P_{e\text{-}p}$	-	0,020	0,020	0,020	0,020	0,227
	Prob. of no Serv. – Empty-Center	$P_{e\text{-}c}$	-	0,020	0,020	0,020	0,020	0,191
	Prob. of no Serv. – Full-Periphery	$P_{f\text{-}p}$	-	0,010	0,010	0,010	0,010	0,128
	Prob. of no Serv. – Full- Center	$P_{f\text{-}c}$	-	0,010	0,010	0,010	0,010	0,101
	Station Density - Center	Δ_c	St./km²	0,015	0,015	0,015	0,015	0,162
	Station Density - Periphery	Δ_p	St./km²	25,0	18,1	12,1	7,9	11,1
	Repositioning period	h	h	12,6	8,7	5,8	3,8	4,4
System Cost	Access Cost	Z_A	€/h	20,0	14,3	9,6	6,3	8,4
	No Service Prob.	Z_{NSP}	€/h	6,1	6,1	6,1	6,1	6,8
	User Cost	Z_{USER}	€/h	1426	1764	2160	2666	€ 2.297
	Operational Cost	Z_O	€/h	150	186	196	209	€ 2.001
	Infrastructure Cost	Z_I	€/h	1576	1951	2355	2875	€ 4.297
	Repositioning Cost	Z_R	€/h	1090	1093	1093	1093	€ 1.093
	Agency Cost	Z_{AGENCY}	€/h	688	943	1160	1425	€ 318

	TOTAL COST	Z	€/h	456	608	714	836	€ 386
Design outputs	Bicycle	m	bicycles	2234	2644	2968	3354	€ 1.797
	Stations	St.	unit	3811	4595	5323	6228	€ 6.094
	Total System Slots	M	unit	13518	17843	20294	23112	6568
	Av. Station Size	-	Slots/st.	1001	1432	1911	2508	419
	Repositioning vans	n	units	12	11	9	8	11671
	Annual Op. C.	-	M€	24836	33005	37650	42997	28
	Annual Fare	-	€	25	23	20	17	25

7.2.3 Value of time

	Parameter	Notation	Unit	3,0	4,0	5,0	6,0	7,0	8,0	9,0
Decision Variables	Prob. of no Serv. – Empty-Periphery	P_{e-p}	-	0,08	0,03	0,02	0,02	0,02	0,02	0,02
	Prob. of no Serv. – Empty-Center	P_{e-c}	-	0,02	0,02	0,02	0,02	0,02	0,02	0,02
	Prob. of no Serv. – Full-Periphery	P_{f-p}	-	0,04	0,02	0,01	0,01	0,01	0,01	0,01
	Prob. of no Serv. – Full-Center	P_{f-c}	-	0,01	0,01	0,01	0,01	0,01	0,01	0,01
	Station Density - Center	Δ_c	St./km²	9,8	11,6	14,0	16,4	18,4	20,4	22,4
	Station Density - Periphery	Δ_p	St./km²	6,3	6,3	6,4	7,9	8,8	9,8	10,6
	Repositioning period	h	h	5,6	5,6	5,8	5,6	5,7	5,8	5,8

System Cost	Access Cost	Z_A	€/h	609	762	883	974	1074	1163	1252
	No Service Prob.	Z_{NSP}	€/h	136	111	115	123	133	143	154
	User Cost	Z_{USER}	€/h	746	873	997	1097	1207	1307	1406
	Operational Cost	Z_O	€/h	1093	1093	1093	1093	1093	1093	1093
	Infrastructure Cost	Z_I	€/h	399	441	491	541	585	631	669
	Repositioning Cost	Z_R	€/h	393	409	426	455	471	486	502
	Agency Cost	Z_{AGENCY}	€/h	1885	1942	2009	2090	2150	2210	2264
	TOTAL COST	Z	€/h	2631	2815	3007	3187	3356	3516	3669
Design outputs	Bicycle	m	bicycles	9622	10522	11484	12169	12876	13585	14133
	Stations	St.	unit	421	473	548	648	727	809	884
	Total System Slots	M	unit	20	19	18	16	15	15	14
	Av. Station Size	-	Slots/st.	16821	18889	20801	22128	23478	24831	25876
	Repositioning vans	n	units	40	40	38	34	32	31	29
	Annual Op. C.	-	M€	26	27	28	30	31	32	33
	Annual Fare	-	€	16,5	17,0	17,6	18,3	18,8	19,4	19,8

	Parameter	Notation	Unit	10,0	11,0	12,0	13,0	14,0	15,0
Decision Variables	Prob. of no Serv. – Empty-Periphery	$P_{e\text{-}p}$	-	0,02	0,02	0,02	0,02	0,02	0,02
	Prob. of no Serv. – Empty-Center	$P_{e\text{-}c}$	-	0,02	0,02	0,02	0,02	0,02	0,02
	Prob. of no Serv. – Full-Periphery	$P_{f\text{-}p}$	-	0,01	0,01	0,01	0,01	0,01	0,01

	Prob. of no Serv. – Full- Center	P_{f-c}	-	0,01	0,01	0,01	0,01	0,01	0,01
	Station Density - Center	Δ_c	St./km²	24,7	25,0	25,0	25,0	25,0	25,0
	Station Density - Periphery	Δ_p	St./km²	11,7	12,7	12,6	13,5	14,3	14,5
	Repositioning period	h	h	5,9	5,7	6,1	5,7	5,8	5,8
System Cost	Access Cost	Z_A	€/h	1323	1436	1426	1556	1675	1802
	No Service Prob.	Z_{NSP}	€/h	163	174	150	185	196	208
	User Cost	Z_{USER}	€/h	1486	1610	1576	1741	1871	2010
	Operational Cost	Z_O	€/h	1093	1093	1090	1093	1093	1093
	Infrastructure Cost	Z_I	€/h	719	726	688	735	743	745
	Repositioning Cost	Z_R	€/h	517	528	456	530	532	532
	Agency Cost	Z_{AGENCY}	€/h	2329	2348	2234	2358	2368	2370
	TOTAL COST	Z	€/h	3815	3958	3811	4099	4240	4380
Design outputs	Bicycle	m	bicycles	14893	14842	13518	14953	15088	15114
	Stations	St.	unit	977	1005	1001	1021	1037	1039
	Total System Slots	M	unit	13	13	12	13	13	13
	Av. Station Size	-	Slots/st.	27327	27236	24836	27465	27741	27795
	Repositioning vans	n	units	28	27	25	27	27	27
	Annual Op. C.	-	M€	34	35	30	35	35	35
	Annual Fare	-	€	20,4	20,6	19,6	20,7	20,7	20,8

7.2.4 Demand concentration

	Parameter	Notation	Unit	1:1	2:1	3:1	4:1	5:1	5:1 Unc
Decision Variables	Prob. of no Serv. – Empty-Periphery	P_{e-p}	-	0,02	0,02	0,02	0,02	0,02	0,02
	Prob. of no Serv. – Empty-Center	P_{e-c}	-	0,02	0,02	0,02	0,02	0,02	0,02
	Prob. of no Serv. – Full-Periphery	P_{f-p}	-	0,01	0,01	0,01	0,01	0,01	0,01
	Prob. of no Serv. – Full- Center	P_{f-c}	-	0,01	0,01	0,01	0,01	0,01	0,01
	Station Density - Center	Δ_c	St./km²	22,9	25,0	25,0	25,0	25,0	28,9
	Station Density - Periphery	Δ_p	St./km²	22,3	16,3	13,1	11,1	9,7	9,9
	Repositioning period	h	h	5,8	5,9	6,1	5,8	5,7	5,9
System Cost	Access Cost	Z_A	€/h	1462	1473	1484	1486	1483	1394
	No Service Prob.	Z_{NSP}	€/h	178	178	179	179	178	176
	User Cost	Z_{USER}	€/h	1640	1651	1662	1665	1662	1570
	Operational Cost	Z_O	€/h	1093	1093	1093	1094	1093	1093
	Infrastructure Cost	Z_I	€/h	792	769	742	712	696	760
	Repositioning Cost	Z_R	€/h	547	532	517	517	512	532
	Agency Cost	Z_{AGENCY}	€/h	2432	2394	2352	2322	2301	2385
	TOTAL COST	Z	€/h	4073	4045	4015	3987	3963	3955
Design outputs	Bicycle	m	bicycles	15749	15562	15337	14671	14409	15360
	Stations	St.	unit	1135	1076	1011	972	944	1065
	Total System Slots	M	unit	12	13	13	13	13	13
	Av. Station Size	-	Slots/st.	28947	28611	28200	26964	26477	28269

	Repositioning vans	n	units	26	27	28	28	28	27
	Annual Op. C.	-	M€	36	35	34	34	34	35
	Annual Fare	-	€	21,3	21,0	20,6	20,3	20,2	20,9

7.2.5 Central unbalance

	Parameter	Notation	Unit	0%	5%	10%	15%	20%
Decision Variables	Prob. of no Serv. – Empty-Periphery	$P_{e\text{-}p}$	-	0,02	0,02	0,02	0,02	0,02
	Prob. of no Serv. – Empty-Center	$P_{e\text{-}c}$	-	0,02	0,02	0,02	0,02	0,02
	Prob. of no Serv. – Full-Periphery	$P_{f\text{-}p}$	-	0,01	0,01	0,01	0,01	0,01
	Prob. of no Serv. – Full-Center	$P_{f\text{-}c}$	-	0,01	0,01	0,01	0,01	0,01
	Station Density - Center	Δ_c	St./km²	25,0	25,0	25,0	25,0	25,0
	Station Density - Periphery	Δ_p	St./km²	13,7	12,0	10,8	9,4	8,4
	Repositioning period	h	h	5,90	6,29	5,50	5,32	4,96
System Cost	Access Cost	Z_A	€/h	1482	1491	1488	1487	1485
	No Service Prob.	Z_{NSP}	€/h	179	179	179	178	178
	User Cost	Z_{USER}	€/h	1661	1670	1666	1666	1663
	Operational Cost	Z_O	€/h	1093	1093	1093	1093	1093
	Infrastructure Cost	Z_I	€/h	736	744	718	708	691
	Repositioning Cost	Z_R	€/h	502	532	608	654	697
	Agency Cost	Z_{AGENCY}	€/h	2330	2369	2419	2455	2481
	TOTAL COST	Z	€/h	3991	4039	4085	4120	4144
Design outputs	Bicycle	m	bicycles	14951	15655	14974	14918	14527
	Stations	St.	unit	1024	989	966	938	919

	Total System Slots	M	unit	13	14	13	14	14
	Av. Station Size	-	Slots/st.	27657	28586	26887	26472	25548
	Repositioning vans	n	units	27	29	28	28	28
	Annual Op. C.	-	M€	33	35	40	43	46
	Annual Fare	-	€	20,4	20,8	21,2	21,5	21,7